Global Flights-to-Safety and Macroeconomic Adjustment in Emerging Markets

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12 October 2020

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February 22, 2021

Abstract

Financial market imperfections point toward large macroeconomic costs associated with 'flights-to-safety' in the absence of policy intervention. I investigate this implication empirically by developing a measure of global flights-to-safety and modelling their impact on emerging markets. Defined as joint tail realizations across developed market risky and safe asset returns, large flights-to-safety map to unexpected tail events and shape future world commodity prices, interest rates and U.S. Dollar fluctuations. In emerging markets, a global flight-to-safety induces a sharp rise in sovereign risk and exchange market pressure followed by a protracted drop in economic activity. These effects are substantially larger than those of U.S. monetary policy shocks and domestic financial shocks. Heterogeneity in adjustment patterns across countries suggest financial disruption as a key transmission channel but also a role for policy intervention: The impact of flights-to-safety on economic activity is amplified in countries realizing sharper adjustment in financial conditions, four times larger in emerging markets with U.S. exchange traded funds, and mitigated through 'leaning against the wind' with international reserves.

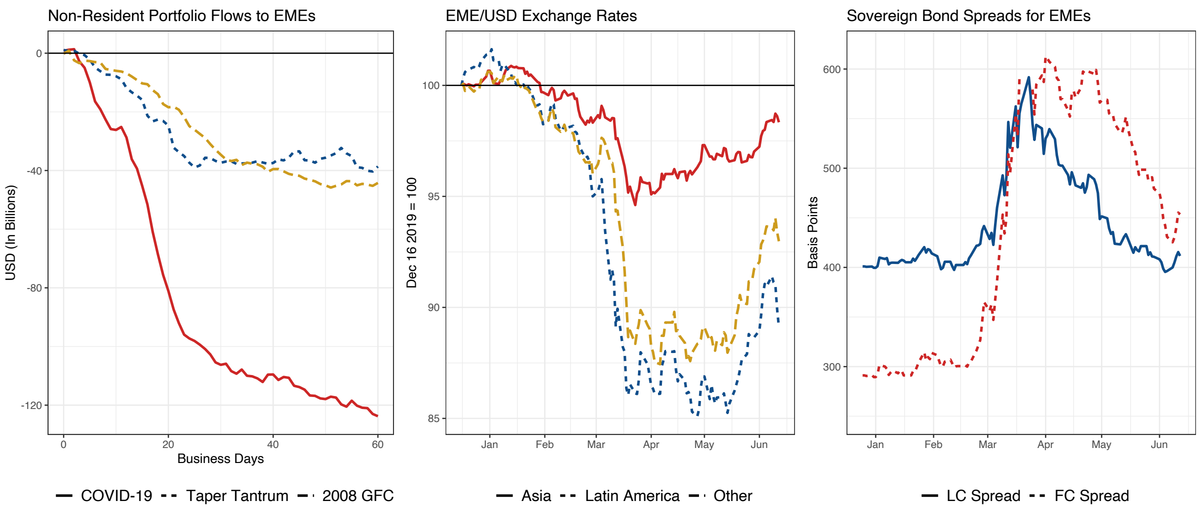
Keywords: Tail Risk, Risk-off, Risk Sentiment, Contagion, International Reserves, Sovereign Risk, Financial Stability, Capital Flows, Macroprudential Policy.
JEL Classifications: F0, F3, F44, F60, G15.

*University of Southern California, Department of Economics, rashadah@usc.edu. The author gratefully acknowledges Joshua Aizenman, Paula Beltran, Katharina Bergant, Caroline Betts, Nathan Converse, Chukwuma Dim, Piti Disyatat, Mai Hakamada, Bada Han, Boris Hofmann, Pablo Kurlat, M. Hashem Pesaran, Romain Ranciere, Alessandro Rebucci, Tatjana Schulze, Alp Simsek, Egon Zakrajšek, David Zeke, participants of the 16th Macro Finance Society Workshop, the IM-TCD Workshop on International Capital Flows and Financial Globalisation, seminar participants at the Office of the Comptroller of the Currency, Federal Reserve Board, MITRE, and the USC Macro Workshops for many helpful comments and discussions. A preliminary version of this paper was first presented at the USC Macro Workshop on June 10, 2020. First draft: October 12, 2020. Previous version titled, "Global Flight-to-Safety Shocks".

1 Introduction

Macroeconomic vulnerabilities to sharp swings in global financial conditions were once more highlighted by the COVID-19 pandemic. Concerns over a global public health crisis left emerging markets indiscriminately exposed, inducing large and volatile capital outflows, currency depreciation, and sharply wider borrowing costs as presented in Figure 1. Despite the uniqueness of the pandemic shock, it shares the signatures of many unanticipated left-tail economic events: a 'flight-to-safety' or alternatively, 'risk-off'. These refer to abrupt, violent swings across financial markets in the form of falling risky asset prices and rotation into safe assets associated with aggressive portfolio rebalancing by global investors. Flights-to-safety directly shape the evolution of the global financial cycle, reflecting both changing risk appetite and expectations over global demand. Flights-to-safety have also increased in severity in the last decade amid an era of unprecedented global liquidity.[1]

Figure 1: COVID-19, Flight-to-Safety, and Emerging Markets



LHS: COVID-19 (Feb 19 2020), Taper Tantrum (May 22 2013), 2008 GFC-Lehman Bankruptcy (September 15 2008). Center: Lower values imply depreciation vis-a-vis the USD. RHS: Local Currency (LC) and Foreign Currency (FC) Spreads. Data Source: 2020 BIS Annual Economic Report.

In this paper, I present a new measure of global shocks intended to capture the intensity of flights-to-safety, differentiating them from other adverse shocks that shape financial markets. These flights-to-safety reflect more primitive shifts in risk appetite or global demand, often both. Specifically, large shocks are measured as joint tail realizations across risky and safe assets identified through sign restrictions. This way, I distinguish shocks which trigger a flight-to-safety from other adverse shocks which similarly effect global

[1]See Figure 3. Note that the 2020 COVID-19 shock at the onset in late February exhibited textbook flight-to-safety features, but by mid-March the indiscriminate selling of both risky and safe assets suggested that it turned to a flight-to-liquidity as it progressed.

financial conditions but do not induce the same flight-to-safety behavior. I then investigate how global flights-to-safety shape economic dynamics in emerging markets, shedding light on potential transmission mechanisms consistent with the theoretical literature.

My proposed methodology to identify flight-to-safety shocks is transparent, easily generalized and flexible. Global flights-to-safety are correlated with benchmark measures of financial conditions such as the VIX index, global realized stock market volatility (Cesa-Bianchi et al. [2020]) an the global financial cycle (Miranda-Agrippino and Rey [2020]), yet imperfectly so because they isolate the component of aggregate financial fluctuations driven by shocks that specifically trigger a flight-to-safety. These flights-to-safety are informative of future commodity prices, interest rates, inflation expectations and U.S. Dollar fluctuations, and map to historically disruptive events. While global flights-to-safety have become a widely studied financial phenomena, the literature has focused on the financial market consequences – how asset prices, capital flows, and financial conditions behave. Meanwhile, there is little evidence linking them to macroeconomic fluctuations despite a strong link suggested by theoretical macro finance models. I show that global flight-to-safety shocks significantly affect measures of economic activity in both the United States and across emerging markets, and on average, the impact is substantially larger than both the effect of U.S. monetary policy shocks and home-grown domestic financial shocks. On a country-by-country basis, however, the extent of these effects are highly uneven. By exploiting this heterogeneity, I shed light on multiple channels through which global flight-to-safety shocks drive macroeconomic fluctuations. Specifically, I show that global flight-to-safety shocks transmit through their effect on domestic financial conditions, are amplified in countries offering U.S. exchange traded funds, and have a substantially weaker impact on economic activity when central banks expend international reserves to 'lean against the wind' during such risk-off episodes. These features are supportive of risk-centric macroeconomic models where asset price volatility affects aggregate demand through shocks to risk premia or by constraining financial intermediaries, and macroprudential central bank policy has the ability to moderate such shocks. Earlier work includes Bernanke et al. [1999] and Mendoza [2010] in closed and open economy settings, respectively, where financial frictions amplify the transmission of shocks. Meanwhile Caballero and Kamber [2019], Caballero and Simsek [2020a] and Caballero and Simsek [2020c] argue that shocks to risk premia, affecting asset prices, can directly cause demand recessions, rather than acting only as an amplification mechanism. In an international setting closely related to this paper, Miranda-Agrippino and Rey [2020], Jeanne and Sandri [2020], and Davis et al. [2020] further show that financial market imperfections lead to real effects. Nearly all of these models share two features in common: They imply a significant relationship between financial market conditions and real activity, along with a buffering role for macroeconomic policy. The results corroborate both implications.

This paper makes two main contributions to the literature. First, there is little consensus on how to systematically measure flight-to-safety or risk-off phenomena. Both regime based (Beber et al. [2014], Baele et al. [2019]) and intensity based (Datta et al. [2017], Chari et al. [2020]) measures of flight-to-safety or 'risk-on/risk-off' have been proposed. Regime-based measures aim to classify periods of extreme safe-risky asset (or currency) price correlations, while intensity based measures provide continuous values which more closely resemble shocks. Other studies rely on off-the-shelf measures of financial stress like the VIX index (De Bock and de Carvalho Filho [2015b], Caballero and Kamber [2019]). I present a new intensity-based approach to measure global flights-to-safety which starts with the key ingredient many of the prevailing measures share: extreme co-movement between safe and risky asset market prices. I then incorporate information from multiple markets while emphasizing tail realizations to more sharply identify flights-to-safety.

Second, I build a multi-country structural VAR with country specific heterogeneity to investigate the financial and macroeconomic implications associated with global flights-to-safety. Focusing on emerging markets which tend to take these shocks as exogenous, I provide new evidence on the transmission of flights-to-safety to macroeconomic fluctuations. More generally, this relates to the broad literature on using panel VARs to evaluate the impact of external global shocks on emerging markets (Uribe and Yue [2006], Akinci [2013], Shousha [2016], Aizenman et al. [2016], Fernandez et al. [2017], Caballero et al. [2019], Obstfeld et al. [2019], Cesa-Bianchi et al. [2020]). Key departures from this literature entail 1) disentangling and focusing on global flights-to-safety specifically over broader measures of global financial stress, 2) while also allowing for country-specific heterogeneity, as in Cesa-Bianchi et al. [2020] to help shed light on the potential transmission mechanisms driving differential macroeconomic adjustment.

I start by presenting a method to recover a daily index of global flight-to-safety intensity based on financial market tail realizations and sign restrictions. First, I recover daily asset price innovations within a asymmetric-GARCH (Generalized Autoregressive Conditional Heteroscedasticity) model of conditional volatility. I take a cross-market approach, applying this procedure across six indices representing major financial asset classes: equities, volatility, exchange rates, government interest rates, and credit. In a second stage, I aggregate these asset-specific price innovations while imposing a sign restriction such that their daily co-movement satisfies the covariance structure observed during a flight-to-safety. I define this as: rising volatility, rising safe asset prices, widening risky credit spreads, and appreciating safe-haven currencies along with depreciating risky assets and risky currencies.

This sign-restriction approach implies that global flights-to-safety are disentangled from more general variation in global financial conditions driven by other types of adverse shocks. Similar conceptually is Jarociński and Karadi [2020], where the authors disentangle types of monetary information shocks by considering the co-movement of equity markets with monetary surprises. The overall aim here is to estimate an otherwise unobservable shock using financial market prices and the co-movement restrictions consistent with flight-to-safety. I show that this measure of global flight-to-safety is significantly associated with both daily and monthly frequency U.S. Dollar appreciations, and the relationship persists after controlling for fluctuations in the VIX index. Moreover, global flights-to-safety are significantly informative of future movements in world commodity prices, interest rates and inflation expectations.

I then model their impact on emerging markets in a multi-country structural VAR. Unlike more traditional panel VAR approaches which assume homogeneous slope coefficients and pool information across countries, I allow for country-specific slope heterogeneity, incorporating interdependencies between emerging markets, while controlling for spillovers from advanced economies, namely the United States. In response to a global flight-to-safety shock, emerging market sovereign spreads sharply widen, exchange market pressure rises (both as currency depreciation and reserves depletion), and a significant contraction in economic activity follows. On average, industrial production contracts by 0.625 standard deviations, or four percent over an 18-month window following a 1-standard deviation global flight-to-safety shock. These results also hold under impulse responses estimated using local projection methods instead of a structural VAR, when using an alternative, model-free measure of global flights-to-safety, and when considering variation in flights-to-safety that are uncorrelated with changes in the VIX. The effects are also asymmetric: the impact of positive flight-to-safety shocks, or risk-off shocks are substantially larger than those of negative shocks, or risk-on shocks. The emerging market response to a 1-standard deviation flight-to-safety is also larger in size than the response to a comparably sized U.S. monetary policy shock or a domestic country-specific financial shock.

The heterogeneity admitted by the modeling approach reveals that macroeconomic adjustment from a global flight-to-safety is far from uniform across countries, and cross-country patterns suggest financial disruption as a key transmission channel, but also a significant role for policy intervention – both key implications of the theoretical models with financial channels. When global flight-to-safety shocks pass through as tighter domestic financial conditions, the subsequent impact on economic activity is much larger. I also show that the impact of global flight-to-safety on economic activity is significantly amplified – roughly by a factor of 4 – in countries which have substantial presence in U.S. traded ETFs, even after accounting for financial openness. This is consistent with specific vulnerabilities arising due to U.S. financial integration, particularly as Converse et al. [2020] shows through ETFs which amplify the global financial cycle in emerging markets. Meanwhile, when monetary authorities more aggressively run down international reserves in response to a flight-to-safety, the following economic contraction is much weaker. This policy of leaning against the wind is most effective when the exchange rate is successfully stabilized, supporting reserves accumulation and management as a macroprudential policy tool.[2]

The overall findings are consistent with theoretical models pointing toward large macroeconomic costs associated with global financial flights-to-safety in the absence of policy intervention. Specifically, my results suggest a potent financial channel in the propagation of these shocks to emerging market economies, but also an important role for domestic policies, namely the accumulation and use of international reserves to 'lean against the wind' during periods of financial turmoil.

The remainder of the paper is structured as follows: Section 2 describes the construction of global flight-to-safety shocks and documents stylized facts. Section 3 investigates how global flights-to-safety shape macroeconomic dynamics in emerging markets. Section 4 explores the heterogeneity in macroeconomic adjustment across countries to shed light on the transmission mechanism. Section 5 concludes. The Online Supplement provides additional details regarding robustness, with Section S3 specifically investigating the role of risk sentiment and global demand components of global flights-to-safety.

2 Global Flights-to-Safety: A Cross-Market Approach

I estimate an index which captures the intensity of global flights-to-safety by 1) pooling information from key international markets spanning major financial asset classes and 2) requiring a particular set of co-movements across these markets to be realized. I specifically consider six markets due to their international presence: The Wilshire 5000 equity index; 10-year U.S. Treasury yields; 10-year German Bund yields; FX Carry index (long the New Zealand Dollar and Australian Dollar while short the Japanese Yen and Swiss Franc); U.S. corporate high yield spreads; the CBOE VIX index. These indices are considered for two main reasons: For broad international coverage across advanced economies, and for coverage across asset classes. The index, therefore, will have representation from major financial asset markets: Equities, volatility, government bonds, corporate credit, and currencies.

The Wilshire 5000 index represents the broad U.S. stock market, while 10-year Treasuries and Bund yields are some of the worlds most recognized safe investments. The FX Carry index captures the relative value of risky, high interest rate, procyclical currencies against safe, low interest rate currencies. The Japanese yen and Swiss Franc act famously as safe havens, appreciating amid turmoil while the Australian and New Zealand Dollar returns tend to be highly procyclical. The U.S. corporate high yield spread reflects the average financing premium faced by U.S. firms that are rated below investment grade.

[2]The macroprudential use of international reserves has also been studied in Aizenman and Lee [2007], Jeanne and Ranciere [2011], Dominguez et al. [2012], Ghosh et al. [2016], Jeanne and Sandri [2020], Davis et al. [2020], Ahmed [2020], Ahmed [2021].

Finally, the VIX index is a common gauge for global investor risk appetite, uncertainty and demand for insuring equity market risk. It specifically measures the option-implied expected forward 1-month volatility of the S&P 500 stock market index.[3]

Table 1: Cross Asset Flight-to-Safety Behavior

Z_{kd}	Underlying	Asset Class	FTS Behavior	w_k(avg)	w_k(PCA)
Z_{1d}	CBOE VIX Index	Volatility	+	1/6	0.17
Z_{2d}	Wilshire 5000 Stock Index	Equities	-	1/6	0.18
Z_{3d}	10-year U.S. Treasury Yield	Government Rates	-	1/6	0.18
Z_{4d}	10-year German Bund Yield	Government Rates	-	1/6	0.19
Z_{5d}	U.S. High Yield Spread	Credit	+	1/6	0.16
Z_{6d}	FX Carry*	Currencies	-	1/6	0.12

*FX Carry is an equally-weighted index long New Zealand Dollar (NZD) and Australian Dollar (AUD) vis-a-vis the the Swiss Franc (CHF) and Japanese Yen (JPY).

A measure of flight-to-safety will be estimated by relying on the cross-asset correlations typically observed during global flights-to-safety. The economics of FTS imply global portfolio rebalancing such that risky assets are sold and safe assets bid in the face of rising uncertainty. To capture this flight-to-safety signature, I define a flight-to-safety or risk-off as a period based on the following sign restrictions over any given trading day:

- Volatility (VIX) rises [$+$]
- Equities fall [$-$]
- Treasury and Bund yields fall [$-$]
- High yield credit spreads rise [$+$]
- Carry currencies (AUD, NZD) depreciate against safe currencies (JPY, CHF) [$-$]

as depicted in Table 1. The precise inverse is defined as risk-on behavior, so the final FTS index will capture both risk-on and risk-off movements.

2.1 Stage 1: Measuring asset market shocks

FTS measure first requires estimating individual asset price shocks before aggregating to the global flight-so-safety index. Denote $r_{kd}, k \in \{1, ...K\}$ as the daily return of asset k over day d. The $K = 6$ assets considered are those mentioned: The VIX, the Wilshire 5000 index, 10-year Treasury yields, 10-year German Bund yields, FX Carry, and U.S. corporate high yield spreads. All returns are in log-differences, except the two government

[3] Notice that four of the six benchmark assets are U.S. centric and therefore, I make the implicit assumption that global FTS are largely reflected in U.S. markets, and more generally across advanced economies. Similar interpretations are taken for the VIX when it is used as a gauge of global risk appetite. While this assumption may be reasonable, global economic centers shift over time. My approach is general enough such that one can easily add more financial benchmarks to the set, (e.g. China) to account for other important or growing economic centers.

yields, which are first-differences. The global FTS index is constructed as an aggregation of normalized daily innovations across these assets. I define daily shocks in each asset by comparing the realized return on day d, r_{kd}, to the square root of the conditional variance forecast for day d (i.e. the ex ante conditional volatility), made on day $d-1$:

$$Z_{kd} = \frac{r_{kd}}{\sqrt{E_{d-1}[\sigma_{kd}^2]}}. \tag{1}$$

This procedure is similar to the approach of conditionally standardizing or devolatizing price returns (Engle [2002] and Pesaran and Pesaran [2010]). A key difference is that I consider the forecasted, or ex ante volatility, while devolatizing traditionally considers realized volatility of the same period as the return, in our case day d. This step serves three important purposes. First, the volatility of returns vary substantially across assets and over time. Standardizing asset returns by their conditional volatility produces a transformation which admits to comparing across assets classes and accounts for regime changes (i.e. volatility clustering). Second, under the assumption that Z_{kd} follows an i.i.d. distribution (it is, after all, a conditional z-score), the probability that return r_{kd} was unexpected rises in $|Z_{kd}|$. From the econometricians perspective, large values of Z_{kd} are increasingly likely to reflect exogenous price movements in the sense that they were unforeseeable. Third, large values of Z_{kd} are naturally interpreted as tail realizations.

While r_{kd} is observed, $E_{d-1}[\sigma_{kd}^2]$ is not and must be estimated. To estimate $E_{d-1}[\sigma_{kd}^2]$, a model which allows for time-varying volatility must be specified. I assume that asset returns are mean zero with time-varying volatility following a GARCH process (Bollerslev [1986]):

$$r_{kd} = \sqrt{E_{d-1}[\sigma_{kd}^2]} Z_{kd}, \quad Z_{kd} \sim (0,1), \tag{2}$$

where the return sequence is mean zero, and split into a stochastic i.i.d component (Z_{kd}) and a time-varying volatility component (σ_{kd}). Notice that our estimates of asset-specific shocks Z_{kd} corresponds to the the exogenous component of asset returns under the specified model. I parameterize Z_{kd} as being drawn from a standard normal distribution, hence conditional returns are normally distributed but the unconditional distribution are allowed to be fat-tailed[4]. Specifically the conditional variance at time d follows a GJR-GARCH(1,1) process:[5]

[4]One can parameterize Z_{kd} as being drawn from a Student-T's distribution which allows for both fat tails in conditional and unconditional distributions, and the results are virtually unchanged.

[5]See Glosten et al. [1993] for the extension of GARCH to GJR-GARCH. Alternatively one could use another model for time-varying volatility, for example stochastic (latent) volatility models. These typically rely on computationally intensive Bayesian approaches to estimate them and further assumptions on prior distributions and estimation design. Despite their differences, GARCH, stochastic volatility, and realized volatility models, three workhorse models of time-varying volatility, perform quite similarly.

$$E_{d-1}[\sigma^2_{kd}] = \omega_k + \alpha_k E_{d-2}[\sigma^2_{k,d-1}] + (\beta_k + \gamma_k \mathbf{I}_{k,d-1}) r^2_{k,d-1}, \text{ where} \tag{3}$$

$$\mathbf{I}_{k,d-1} = \begin{cases} 0 & \text{if } r_{k,d-1} > 0 \\ 1 & \text{if } r_{k,d-1} < 0. \end{cases} \tag{4}$$

The conditional volatility model under a GJR-GARCH extends the classical GARCH framework by allowing for asymmetric volatility, a well-known stylized fact of financial asset returns where the conditional variance of an asset is correlated with returns. The expected or ex ante volatility for day d conditional on day $d-1$ information is computed as:

$$\sqrt{E_{d-1}[\sigma^2_{kd}]} = \sqrt{\omega_k + \alpha_k E_{d-2}[\sigma^2_{k,d-1}] + (\beta_k + \gamma_k \mathbf{I}_{k,d-1}) r^2_{k,d-1}}. \tag{5}$$

Referring back to Equation 1, I recover shocks to asset k by dividing its observed realization on day d with the ex ante conditional volatility (Equation 5). In other words, we simply ask: *to what degree was the realized move justified under the prevailing (ex ante) forecast distribution?* Larger values imply tail realizations, and equivalently returns which are more likely to be unforeseeable and less likely to be generated from the ex ante distribution.

With the Z_{kd} for all 6 components estimated, the global daily FTS index (FTS_d) is constructed as the rotated cross-section average on each day d:

$$FTS_d = (w_1 Z_{1d} - w_2 Z_{2d} - w_3 Z\_w_4 Z_{4d} + w_5 Z_{5d} - w_6 Z_{6d}) \mathbf{1}_d, \quad \sum_{k \in K} w_k = 1, \tag{6}$$

where the rotations ensure that positive values of FTS_d coincide with fight-to-safety or risk-off, and negative values coincide with risk-on episodes. Hence, the shocks (Z_{kd}) corresponding to the VIX and high-yield credit spreads are added, while the rest are subtracted. I apply equal weights $w_a = 1/6$ but more generally, one can assign arbitrary weights w_k across assets. Similarly, an estimate of FTS_d can be obtained by taking the first principal component across asset shocks Z_{kd}. The implicit weights assigned via PCA are reported in Table 1 under $w_k(PCA)$. In practice, there is very little difference between estimates of FTS_d obtained via PCA or equal weighting. Specifically, the FTS_d estimated as the cross-section average shares a correlation of over 0.98 with the PCA approach. This is because the cross-section average and 1st principal component asymptotically converge to the same measure under true factor structure (likely in our case with financial market returns, Westerlund and Urbain [2015]). The added benefit of taking cross-section averages is that it can be calculated each period without requiring information from the entire sample. By contrast, a key advantage of the PCA approach is that it can "selflearn" weights in high-dimensional settings when the set of variables in Z_{kd} becomes large.

2.2 State 2: Imposing the flight-to-safety sign restrictions

To then identify flight-to-safety shocks, FTS_d is multiplied by an indicator $\mathbf{1}_d$ which takes a value of 1 if that day's cross-asset co-movement was consistent with either flight-to-safety/risk-off or risk-on, and 0 otherwise (the flight-to-safety conditions shown in Table 1.):

$$\mathbf{1}_d \begin{cases} 1 & \text{if } \{Z_{1d}, Z_{5d}\} > c \cap \{Z_{2d}, Z_{3d}, Z_{4d}, Z_{6d}\} < -c \quad \textit{`Risk-Off'} \\ 1 & \text{if } \{Z_{1d}, Z_{5d}\} < -c \cap \{Z_{2d}, Z_{3d}, Z_{4d}, Z_{6d}\} > c \quad \textit{`Risk-On'} \\ 0 & \text{otherwise.} \end{cases} \tag{7}$$

This way, I impose the sign restriction condition that all 6 asset returns move in the direction consistent with flight-to-safety, with the size of the move necessarily larger than some threshold c. If asset price movements do not satisfy this joint condition, there is no flight-to-safety, and $FTS_d = 0$. If the set of sign restrictions is satisfied, the size of FTS_d is continuous, and can be positive ('risk-off') or negative ('risk-on'). As a baseline, I set $c = 0$, meaning a flight-to-safety is identified simply based on sign, regardless of the size of the moves. One issue with this method is that some days may satisfy the FTS condition simply by random chance, and likely realize low values of FTS_d, though this becomes increasingly unlikely as the number of sign restrictions increase. Taking a more conservative threshold for c, accounts for both the direction and size of cross-asset moves. Considering this alternative, I also set a threshold of $c = 1$, meaning that all components must have $|Z_{kd}| > 1$ on a given day (at least a 1-sigma) and also move in the direction consistent with flight-to-safety to trigger as an FTS. Note also that the threshold c can be further generalized, setting different c for each asset price series Z_{kd}. Moreover, given a particular target outcome variable (e.g. GDP growth), one could estimate a threshold c using maximum likelihood methods (MLE) as in Chudik et al. [2020]. For simplicity and in this particular case because all shock series are standardized I consider the same threshold c across Z_{kd}.

Finally, the daily FTS index FTS_d can be aggregated to monthly frequency, FTS_t:

$$FTS_t = \sum_{d=1}^{D(t)} FTS_d(t), \tag{8}$$

where $D(t)$ is the number of days in month t, and $FTS_d(t)$ denote daily global fight-to-safety measures corresponding to month t. By summing the daily values of FTS_d, which can be positive (risk-off), negative (risk-on) or zero (non-event), each monthly value of FTS_t can be interpreted as the net of the daily positive and negative daily FTS values. A large positive monthly value of FTS_t indicates that month had either/several large global flight-to-safety days (risk-off) relative to risk-on days and days which were neither risk-on or risk-off.

Table 2: FTS Index: Sensitivity Analysis

	Correlation with	
Excluding:	daily FTS_d	monthly FTS_t
CBOE VIX Index	0.95	0.96
Wilshire 5000 Stock Index	0.97	0.97
10-year U.S. Treasury Yield	0.97	0.96
10-year German Bund Yield	0.92	0.93
U.S. High Yield Spread	0.96	0.95
FX Carry	0.88	0.89

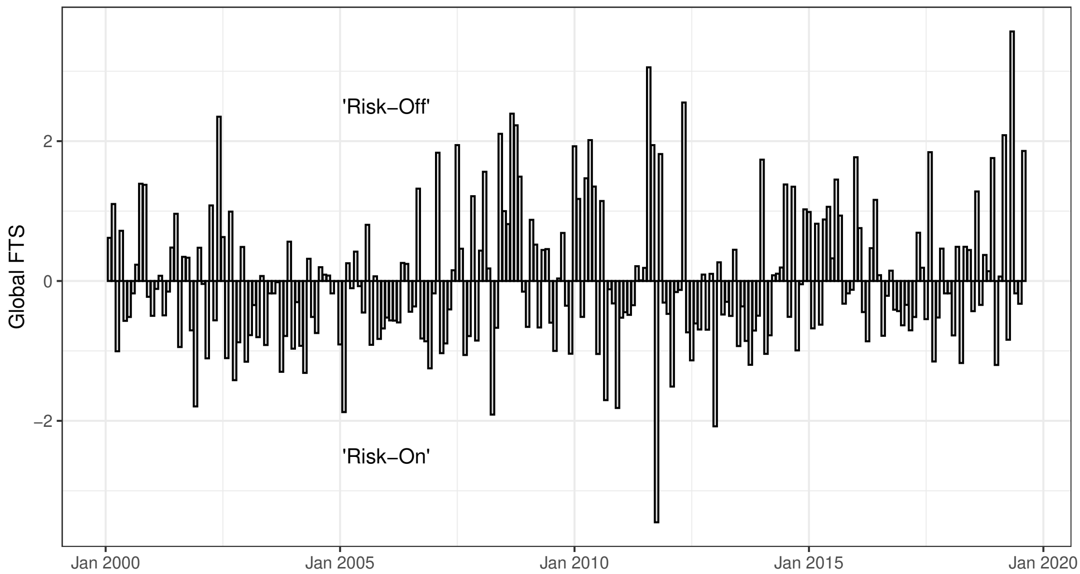
Leave-one-out analysis constructs the FTS_d and FTS_t indices but only aggregating four of the five assets, excluding one at a time. Then the correlations are estimated against the full FTS index calculated with all five assets, to test whether the index is sensitive to leaving any particular asset out of the calculation. Final row excludes two components: high yield spreads and the VIX index.

Because only six assets are in the set K which constructs the FTS index, it's important to assess how sensitive the index is to excluding any single asset. I provide results from a leave-one-out analysis as a robustness check in Table 2, showing that both the daily and monthly FTS series remains highly correlated with series constructed as an aggregate of five of the six assets. Re-computing the index while excluding any of the assets maintains a correlation of 0.89 or greater with the monthly FTS index constructed from all six assets, and 0.88 or higher for the daily index. The inclusion of safe assets is also important for distinguishing flights-to-safety from indicators of the Global Financial Cycle, estimated as the common factor from a broad array of risky asset prices (Rey [2015] and Miranda-Agrippino and Rey [2020]) and do not consider safe asset prices.

I omit gold from the FTS index because I wish to only consider financial market assets. There are several additional reasons: First, the price of gold tends to be strongly determined by factors like its finite supply and the real interest rate. Second as a commodity, gold prices are disproportionately affected by global demand forces versus traditional financial assets, and its market size is dwarfed by the size of other safe asset markets. As a result the allocation of major global investors and intermediaries to gold is disproportionately small in comparison to safe financial assets. The U.S. Dollar, another safe asset, I also omit from the flight-to-safety index for similar reasons. The value for the Dollar is driven by several factors, being the benchmark trade invoicing currency and also the global reserve currency. I will show, however, that the U.S. dollar significantly appreciates during a flight-to-safety, consistent with its safe-haven status, and I consider both gold and the USD as outcome variables when estimating the impact of flights-to-safety on world prices.

2.3 Global flight-to-safety: properties and stylized facts

Figure 2: Time-Series of Global Flights-to-Safety (FTS_t)

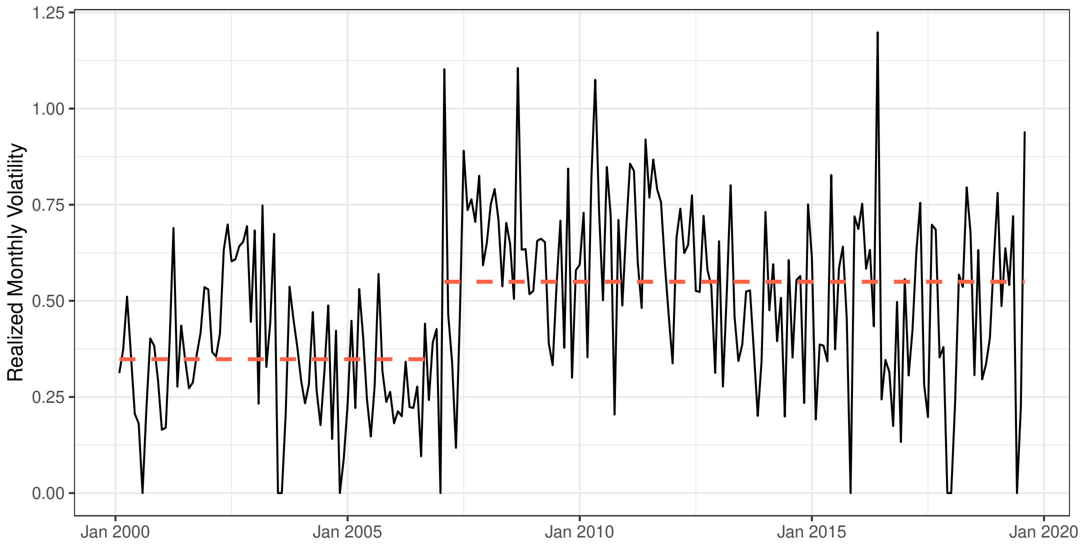


First order auto-correlation = -0.01. Series is normalized to have unit standard deviation.

From January 2000 through August 2019, of the 5,130 days in the sample, 9.6% are consistent with a flight-to-safety or 'risk-off', with 9.6% co-moving in a way consistent with 'risk-on'. Note that these proportions do not say anything about the size of the moves (recall $c = 0$). Risk-off days are also particularly special in the sense that asset price moves are significantly larger – statistically and economically – than usual. For the Wilshire 5000 stock index, the average daily negative return is -0.7%. on a risk-off day, when negative equity returns are accompanied by rising volatility, falling bond yields, rising credit spreads and depreciating risky currencies the average daily Wilshire 5000 return doubles to -1.4%. Similar patterns apply across the other markets. When the VIX index rises, it rises on average 5.3%. On a risk-off day, it rises on average 8.4%.

A time-series of monthly FTS shocks is shown in Figure 2. Unlike the standard VIX index or changes in the VIX, neither daily nor monthly measures of FTS shocks (FTS_d or FTS_t) exhibit significant serial correlation - an important feature which should be necessary, but not sufficient, in a measure of global FTS shocks. The volatility of FTS shocks have also markedly increased since 2007 (Figure 3). Each month the realized volatility is computed by taking the standard deviation of daily FTS_d shocks within that month. The volatility of FTS shocks after February 2007 is roughly 60% larger than before 2007.

Figure 3: Realized Monthly Volatility of Daily Global Flight-to-Safety Shocks



Each month's realized volatility of FTS is computed as the standard deviation of daily values of FTS_d for each month. Structural break occurs in February 2007.

2.4 FTS and other measures of financial stress

The way FTS shocks are designed, they can be interpreted as a subset of more general global financial fluctuations: Those which are 1) abnormally large and 2) satisfy the fight-to-safety sign restrictions. Figure 4 shows that the FTS index (x-axis) are indeed correlated with other measures of financial stress, but imperfectly so. These imperfect correlations suggest certain overlapping as the indices all respond to shocks that generate flights-to-safety. However, several types of adverse shocks that do *not* generate a flight-to-safety are still captured as fluctuations in broad measures of financial stress: Monetary policy shocks, stagflationary shocks, liquidity crunches, non-fundamental shocks.[6] Therefore, the FTS index more cleanly separates a specific type of shock which generates a flight-to-safety pattern. This is especially important if we believe that shocks generating distinct patterns across financial markets bear different economic implications and signal.

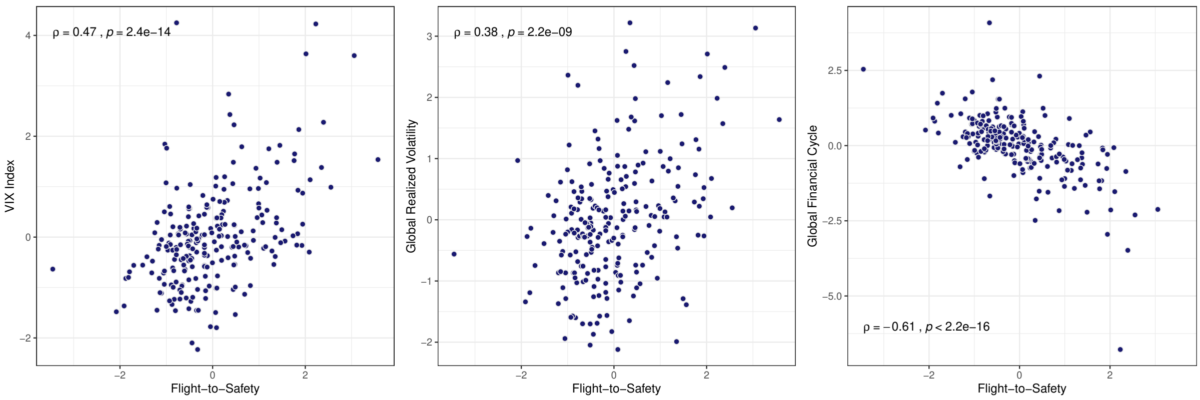
Global flights-to-safety can explain roughly 22% of the variation in log changes in the VIX (correlation of 0.47). The measure $GVOL_t$ is the change in logged global average equity realized volatility in the spirit of Cesa-Bianchi et al. [2020].[7] Monthly FTS can

[6] For instance, contractionary monetary policy shocks and liquidity shocks may result in falling equity prices and *rising* bond yields. A similar co-movement approach to disentangle shocks is used in Jarociński and Karadi [2020] who disentangle monetary information shocks using co-movements with equity returns.

[7] The measure is calculated by first computing monthly equity realized volatility from daily stock market index returns across 32 countries, and then taking the cross-section average to arrive at a global average realized volatility index. Finally for consistency, the measure is logged and then first-differenced.

explain roughly 14% of the variation in $GVOL_t$ (correlation of 0.38). FTS_t is also imperfectly correlated with monthly changes in the global financial cycle indicator of Rey [2015] and Miranda-Agrippino and Rey [2020], $GFCY_t$, though the correlation is stronger than that between FTS_t and $GVOL_t$ or that between FTS_t and changes in the logged VIX index. Roughly 37% of the variation in $GFCY_t$ is explained by global flights-to-safety (correlation of -0.61). Particularly interesting is that FTS, composed from just 6 components, exhibits the degree of correlation that it does with the Global Financial Cycle, which is estimated using over 1,000 asset prices series.

Figure 4: Global Flight-to-Safety Shocks and other measures of Global Financial Stress



LHS: Monthly changes in logged VIX index on the y-axis. Center: Monthly changes in logged global realized volatility, $GVOL_t$ from Cesa-Bianchi et al. [2020] on the y-axis. RHS: Monthly changes in the Global Financial Cycle, $GFCY_t$ from Miranda-Agrippino and Rey [2020] on the y-axis.

These correlations weaken further when increasing the threshold to $c = 1$ which more conservatively identifies flight-to-safety episodes as tail shocks.

2.5 Events underlying the largest flights-to-safety

Comparing extreme values of the FTS index shows that it indeed captures global tail risk. Table A.1 provides a list of dates between 2000 and 2020 that, based on the daily measure FTS_d, are identified as the largest flights-to-safety. The global nature of these shocks become apparent: 'Brexit' (2016), 'Chinese Correction' (2007), U.S. President Trump political controversies (2017), the Lehman bankruptcy (2008), and the Arab Spring (2011) round out the top five daily global flights-to-safety. If we included early 2020 in the calculation, January 27 and February 24, 2020, the onset of the COVID-19 global pandemic, would have both scored within the top ten largest FTS_d readings since 2000, specifically the tenth and fourth largest, respectively. Using a different methodology, a similar list is reported in De Bock and de Carvalho Filho [2015a]. Several flight-to-safety episodes flagged by FTS_d are shared in their list, even with different approaches. None of the ten largest global FTS shocks correspond with the largest U.S. stock market crashes. Table

A.2 lists the top 10 largest daily stock market percent declines between the same period Most of the largest stock market crashes occurred during the 2008 Global Financial Crisis, and another the popping 2000 Tech Bubble. Table A.3 shows the top 10 largest percent changes in the VIX index – three overlap with the top 10 daily largest FTS shocks. The largest VIX shock reflects the 'Volmageddon' (2018), considered by many practitioners as a technical, non-fundamental event caused by overcrowded short volatility positions, highlighting the potential for non-fundamental movements in financial stress indicators.

2.6 Global fights-to-safety, the U.S. Dollar, and world prices

Table 3: Global Flights-to-Safety and U.S. Dollar Appreciation

	Daily Returns				*Monthly Returns*			
	G10/USD		EM/USD		G10/USD		EM/USD	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	−0.001	−0.001	0.008*	0.008*	−0.021	−0.021	0.115	0.119
	(0.006)	(0.006)	(0.005)	(0.005)	(0.114)	(0.113)	(0.077)	(0.076)
Lagged USD	−0.011	−0.012	0.061**	0.053**	0.363***	0.344***	0.403***	0.386***
	(0.016)	(0.016)	(0.025)	(0.025)	(0.059)	(0.061)	(0.067)	(0.070)
$\Delta \ln VIX$	0.003***	0.0005	0.015***	0.007***	0.023***	0.015	0.040***	0.034***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.009)	(0.009)	(0.007)	(0.008)
FTS		0.034***		0.091***		0.278**		0.243***
		(0.009)		(0.007)		(0.118)		(0.092)
Observations	5,129	5,129	5,129	5,129	234	234	234	234
R^2	0.003	0.007	0.081	0.127	0.171	0.187	0..366	0.386
Adjusted R^2	0.002	0.006	0.081	0.126	0.164	0.176	0.361	0.378

Robust standard errors with *,**,*** corresponding to 10, 5, and 1 percent significance, respectively. USD returns are computed as log-changes from the previous period. G10 index is the USD return vis-a-vis an equal-weighted basket of currencies of: New Zealand, E.U., United Kingdom, Australia, Switzerland, Sweden, Norway, Denmark, Japan, Canada. EM index is the USD return vis-a-vis an equal weighted basket of currencies of: South Korea, Mexico, Brazil, India, Malaysia, South Africa, Taiwan, Thailand, Sri Lanka. FTS is normalized to unit variance, while other variables are in percentages.

Table 3 reports daily and monthly regressions of U.S. Dollar log returns on its own lagged returns, changes in the VIX index, and the FTS index. I consider the Dollar vis-a-vis an equally weighted basket of advanced (G10) and emerging market (EM) economies separately. The results are consistent with the Dollar's role as a global safe asset. When including the VIX and excluding the FTS index (columns 1, 3, 5, 7), USD appreciation is significantly associated with positive innovations in the VIX. However, the FTS index is significantly and even more powerfully associated with Dollar appreciations. While both the VIX and FTS are highly significant for the EM/USD exchange rate, the VIX loses it's explanatory power once the FTS is introduced in the G10 equations. This result implies that jumps in the VIX alone are not sufficiently capturing conditions that warrant a flight to the Dollar. Rather, G10 Dollar appreciations are only associated with the VIX when the VIX rises *amid* a flight-to-safety.

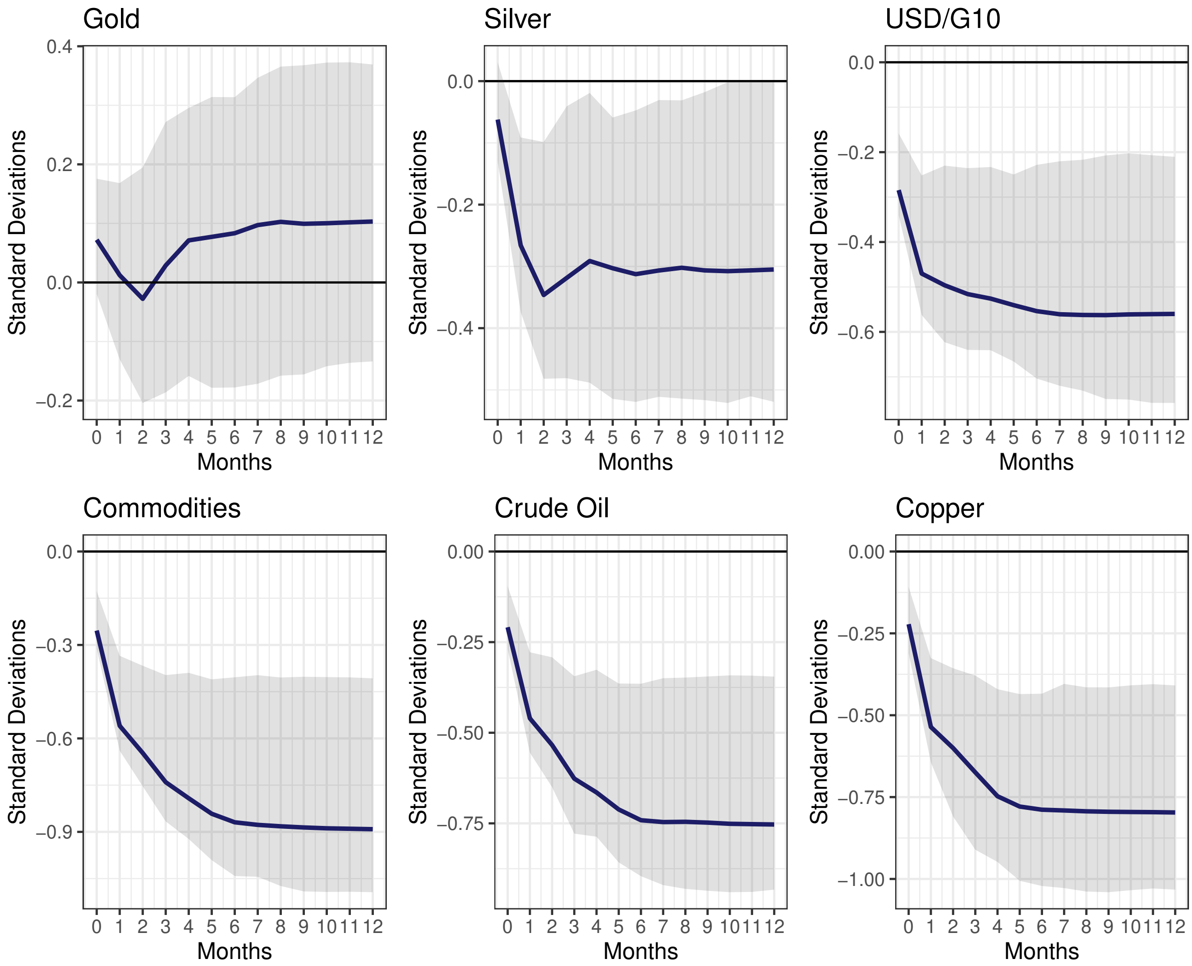
To explore the responses to a global flight-to-safety across a broad spectrum of world prices, I estimate a second-order structural vector auto-regression (SVAR) of monthly log-differences of U.S. short and medium term yields, USD exchange rates, commodities, and U.S. inflation expectations where FTS shocks, FTS_t, are identified recursively: FTS shocks are ordered first, such that they impact all other variables contemporaneously, consistent with the exogenous nature of unusual or unexpected events which trigger flights-to-safety. Because we model the response to FTS shocks, the ordering of the remaining variables does not matter. Figure 5 traces the impulse responses of a 1-SD FTS shock on a variety of commodity prices, gold, and the USD exchange rate vis-a-vis the G10. The solid line is the response to a 1-SD FTS shock, FTS_t, with shaded areas indicating 90% bootstrapped confidence bands. Figures A.1 and A.2 provide additional IRFs for U.S. interest rates, inflation expectations and additional commodity prices.

Most responses exhibit significant adjustment for several months following an FTS shock, U.S. yields and market-based inflation expectations fall along the entire maturity curve. Commodity prices fall and the U.S. Dollar appreciates in response to an FTS shock, both in time 0 and subsequent months. The response of commodities is sharp across metals and energy. The impact of FTS shocks are also apparent in some soft commodities (Figure A.2) like soybeans, one of the largest Chinese imports. These results further suggest that flights-to-safety are not pure shocks to risk aversion, rather there is an important change in global demand (i.e. physical risk) that occurs. The effect on gold is statistically indifferent from zero and the impact on silver is significant but relatively small. This may be somewhat surprising given that some view precious metals as safe havens. However the differential impact on the U.S. Dollar and gold highlights the nature of gold being a safe asset but also a commodity with industrial use. Because FTS also indicate dropping global demand, the demand effect offsets the risk premia effect on gold prices, resulting in the null average response. By contrast, the U.S. Dollar appreciates when faced with both adverse global demand or risk aversion. I show this in Section S3, where I attempt to separate the excess risk sentiment and global demand components embedded in global FTS shocks, subject to a number of assumptions.

2.7 Robustness

The responses of world prices to a global flight-to-safety are robust. Figure A.3 shows that fluctuations in FTS_t that are uncorrelated with changes in the VIX index still have signifiant information content, highlighting the special nature of flights-to-safety beyond aggregate fluctuations in the VIX index. Figure A.4 sets the FTS condition threshold

Figure 5: Response to a 1-Standard Deviation FTS Shock



Cumulative response (in standard deviations) to a 1-standard deviation structural flight-to-safety (FTS) shock, FTS_t. 90% bootstrapped confidence bands. Negative change in USD/G10 is U.S. Dollar appreciation.

to $c = 1$, so not only do all 6 assets need to move in specific directions, but they must all move in excess of 1 standard deviation, emphasizing tail events. Finally Figure A.5 orders the FTS shock in the SVAR last, allowing it to only impact world prices with a lag rather than contemporaneously. The benchmark results broadly hold under this setup as well.

For additional robustness, I also propose a model-free estimator of global FTS shocks in Section S2 of the Online Appendix. This simple approach identifies FTS shocks as changes in the log VIX index on days which satisfy the flight-to-safety condition mentioned previously. These daily VIX changes amid risk-on/risk-off are then summed to a monthly aggregate FTS series, which turns out to be highly correlated with the baseline FTS shock series, FTS_t.

3 Global Flights-to-Safety and Emerging Markets

Recent debate and research focuses the consequences of global financial shocks on emerging markets (EMs), many of which are left particularly vulnerable from growing financial integration. I revisit this issue, specifically to evaluating the dynamics of emerging markets in response to a global flight-to-safety shock. I collect monthly data on sovereign spreads and industrial production across 34 emerging markets from 2000 to 2019.[8] I build on several recent studies have investigated the global transmission of world financial shocks on EM dynamics (Uribe and Yue [2006], Akinci [2013], Caballero et al. [2019], Kalemli-Ozcan [2019], Cesa-Bianchi et al. [2020], Obstfeld et al. [2019]). The traditional modeling approach used is a panel regression or VAR which estimates average effects and impulse response functions (IRF) to a global shock by pooling information across all countries. While pooling has the advantage of increasing statistical power, it ignores vital heterogeneity across countries, which surely exists among EMs. A key difference in my modeling approach is that I allow for country-specific heterogeneity, following an approach similar to Cesa-Bianchi et al. [2020]. I further show that this heterogeneity can be used to shed light on potential transmission mechanisms through which global shocks transmit to the real economy.

In view of this consideration, I propose a heterogeneous multi-country VAR which combines elements from the large VAR literature (Global Vector Autoregressive (GVAR) Pesaran et al. [2004] and Factor-augmented Vector Autoregressive (FAVAR) Bernanke et al. [2005]). Like the benchmark panel VAR, it can be used to report average effects by pooling results across countries. However, like Fernandez et al. [2017] and Cesa-Bianchi et al. [2020], my approach builds on previous analyses by also allowing for country-specific heterogeneity. Key modeling challenges of multi-country economic systems include accounting for 1) global common factors 2) network effects or spillovers between countries 3) spillovers from advanced countries to emerging markets, and 4) heterogeneous transmission of shocks. Consider the baseline model which incorporates these features:

$$\begin{bmatrix} \Delta s_{i,t} \\ \Delta y_{i,t} \\ \Delta \mathcal{S}_{i',t} \\ \Delta \mathcal{Y}_{i',t} \\ \Delta \mathcal{Y}_{US,t} \\ FTS_t \end{bmatrix} = \begin{bmatrix} \theta_i^s \\ \theta_i^y \\ \theta_i^{\mathcal{S}} \\ \theta_i^{\mathcal{Y}} \\ \theta_i^{US} \\ \theta_i^V \end{bmatrix} + \Phi_i(L) \begin{bmatrix} \Delta s_{i,t-1} \\ \Delta y_{i,t-1} \\ \Delta \mathcal{S}_{i',t-1} \\ \Delta \mathcal{Y}_{i',t-1} \\ \Delta \mathcal{Y}_{US,t-1} \\ FTS_{t-1} \end{bmatrix} + \begin{bmatrix} u_{i,t}^s \\ u_{i,t}^y \\ u_{i',t}^{\mathcal{S}} \\ u_{i',t}^{\mathcal{Y}} \\ u_{i,t}^{US} \\ v_t \end{bmatrix}, \tag{9}$$

where $\Delta s_{i,t}$ is the change in the log sovereign spread – a proxy for domestic financial

[8] Data details are found in Section S1.

conditions – of country i over month t. Country i's year-over-year change in industrial production (IP) in month t is given by $\Delta y_{i,t}$. It's easy to see that a model with just these two variables represents a classic VAR(L) model. Country-specific lag polynomials are expressed as $\Phi_i(L)$ of finite order ℓ. I set the number of lags equal to $\ell = 4$ months. The specification is extended by modeling cross-country linkages through $\Delta\mathcal{S}_{i',t}$ and $\Delta\mathcal{Y}_{i',t}$. These are cross-section averages of changes in the log sovereign spread and year-over-year IP growth over all countries excluding country i. Specifically,

$$\Delta\mathcal{S}_{i',t} = \Delta s^*_{i',t} = \sum_{i' \neq i} w^s_{i'} \Delta s_{i',t}, \qquad \sum_{i'=1}^{N-1} w^s_{i'} = 1,$$

$$\Delta\mathcal{Y}_{i',t} = \Delta y^*_{i',t} = \sum_{i' \neq i} w^y_{i'} \Delta y_{i',t}, \qquad \sum_{i'=1}^{N-1} w^y_{i'} = 1,$$

where $\Delta s^*_{i',t}$ is a weighted average of the spread change for countries not including i, $\Delta s_{i',t}$, weighted by $w^s_{i'}$. I set equal weights ($w^s_{i'} = 1/(N-1)$ for all i'), therefore $\Delta s^*_{i't}$ can be interpreted as the cross-section average of sovereign spread changes, exclusive of country i. The same is done for $\Delta\mathcal{Y}_{i,t}$, except I exclude Iraq from the calculations given large outlier values driven by the Iraq War in the early 2000's. Other approachs to obtaining weights would be to apply GDP weights, bilateral trade-weights, capital flow weights, or estimateing them via PCA for $w^s_{i'}$.[9] However, in this particular setting, because cross-country correlations are high, these alternatives make no practical difference.

Including these global averages admit for cross-country interdependencies without running into the 'Curse of Dimensionality' issue most large VARs face (hence, also admitting to a GVAR interpretation). For example, $\Delta\mathcal{S}_{i',t}$ and $\Delta\mathcal{Y}_{i',t}$ can be thought of as the inclusion of lagged spreads and IP growth for all other countries in the equations for country i. Without any coefficient restriction, estimating a VAR(4) would entail the addition of $33 \times 4 \times 2 = 264$ additional lagged variables, exceeding the number of observations. However, including cross-sectional averages imply a coefficient restriction such that lag l spreads and IP growth from all other countries in country i's equation have coefficients equal to $\Phi_i(L)\frac{1}{N-1}$. I also include $\Delta\mathcal{Y}_{US,t}$ changes in U.S. economic activity, measured using the Chicago Fed National Activity Index (CFNAI) to account for spillovers between advanced economies and emerging markets.

Finally, FTS shocks FTS_t enter the system as a common variable across all countries to which countries respond differentially (as reflected in the country-specific coefficients θ^V_i), and the shock is identified recursively. That is, FTS_t can be viewed as a common factor that unlike $\mathcal{S}_{i',t}$ and $\Delta\mathcal{Y}_{i',t}$ is completely external to the system. Recall that FTS_t is measured from financial variables either based out of the U.S. or advanced economies,

[9] I test both and the factor estimated via averages and that via PCA are highly correlated, close to a coefficient of 1.

while the endogenous variables in Equation 9 belong to emerging markets except for $\Delta\mathcal{Y}_{US,t}$.

3.1 Estimating the multi-country SVAR and impulse responses

The shock FTS_t is structural, in that it is identified under the recursive assumption that FTS_t contemporaneously affects fast-moving financial variables $\Delta s_{i,t}$ and $\Delta\mathcal{S}_{i',t}$, while slower-moving macroeconomic variables $\Delta y_{i,t}$, $\mathcal{Y}_{i',t}$ and $\mathcal{Y}_{US,t}$ respond to FTS shocks with a 1-month lag. It is, after all highly plausible that a global financial shock passes through to country i's financial conditions while an idiosyncratic shock to country i does not trigger a global flight-to-safety – so long as country i is not a dominant country in the economy.[10] Within a sample of emerging markets this assumption is reasonably satisfied. The recursive assumption related to $\Delta y_{i,t}$, $\mathcal{Y}_{i',t}$ and $\mathcal{Y}_{US,t}$ requires the FTS shock variable FTS_t to be contemporaneously orthogonalized against the three slow-moving economic activity variables. The results of the impulse response analysis are robust to alternative ordering restrictions, specifically one such that FTS_t contemporaneously affects all other variables but no other variable contemporaneously affects FTS_t.

The large T dimension of the data allows the multi-country SVAR to be estimated country-by-country, estimating country-specific SVARs for 34 emerging markets. This estimation procedure is akin to estimating a Global VAR (Pesaran et al. [2004], Chudik and Pesaran [2016]) with similar approaches also being applied in Fernandez et al. [2017] and Cesa-Bianchi et al. [2020]. The heterogeneous modeling approach still allows estimation of average or pooled effects as done in traditional panel models. Estimating the average IRF over the panel is simple using the Mean Group (MG) estimator of Pesaran and Smith [1995] and Chudik and Pesaran [2019].[11] Following Cesa-Bianchi et al. [2020], the horizon h mean group, or average, impulse response function for the endogenous variable, denoted X_{it}, to a 1-SD FTS shock is computed as:

$$\begin{aligned} MGIRF(h) &= \frac{1}{N}\sum_{i=1}^{N} E[X_{i,t+h}|v_t = 1, \omega_{t-1}] - \frac{1}{N}\sum_{i=1}^{N} E[X_{i,t+h}|v_t = 0, \omega_{t-1}] \\ &= \frac{1}{N}\sum_{i=1}^{N} E[X_{i,t+h}|v_t = 1, \omega_{t-1}], \quad (10) \end{aligned}$$

[10] An excellent example corroborating this assumption is the case of Chile in 2019, suffering from increasing political unrest and protest. While these events disrupted Chile's domestic financial and economic conditions, it did not trigger a reaction across global financial markets. By contrast, a few months later, panic over COVID-19 induced a global financial market shock which severely impacted Chile among many other countries in an indiscriminate fashion.

[11] Alternatively, the Common Correlated Effects Estimator (CCE) of Pesaran [2006] and Chudik and Pesaran [2015] can also be applied.

where $E[X_{i,t+h}|v_t = 1, \omega_{t-1}]$ is the horizon h impulse response of country i, denoted as the conditional expectation of $X_{i,t+h}$ given a 1-SD structural FTS shock ($v_t = 1$), and ω_{t-1} denotes the full information set available as of time $t-1$. Intuitively, the impulse response function of Equation 10 examines how $X_{i,t+h}$ responds to a 1-standard deviation FTS shock at time t given the information available at time $t-1$, comparing it to a counterfactual scenario of no FTS shock ($v_t = 0$) at time t with the same information available at time $t-1$. The associated non-parametric cross-sectional standard errors computed as:

$$SE(h) = \sqrt{\frac{1}{N}\frac{1}{N-1}\sum_{i=1}^{N}\Big(E[X_{i,t+h}|v_t = 1, \omega_{t-1}] - MGIRF(h)\Big)^2}. \tag{11}$$

It can be easily seen that the MG IRF is simply the cross-section average of all i country-specific IRFs, each being denoted $E[X_{i,t+h}|v_t = 1, \omega_{t-1}]$, at each horizon h. 95% dispersion intervals for each horizon h which I report in the results are equal to

$$MGIRF(h) \pm 1.96 \times SE(h). \tag{12}$$

These methods have been applied successfully to large, heterogeneous macroeconomic panel data of similar size to address a variety of research questions.[12]

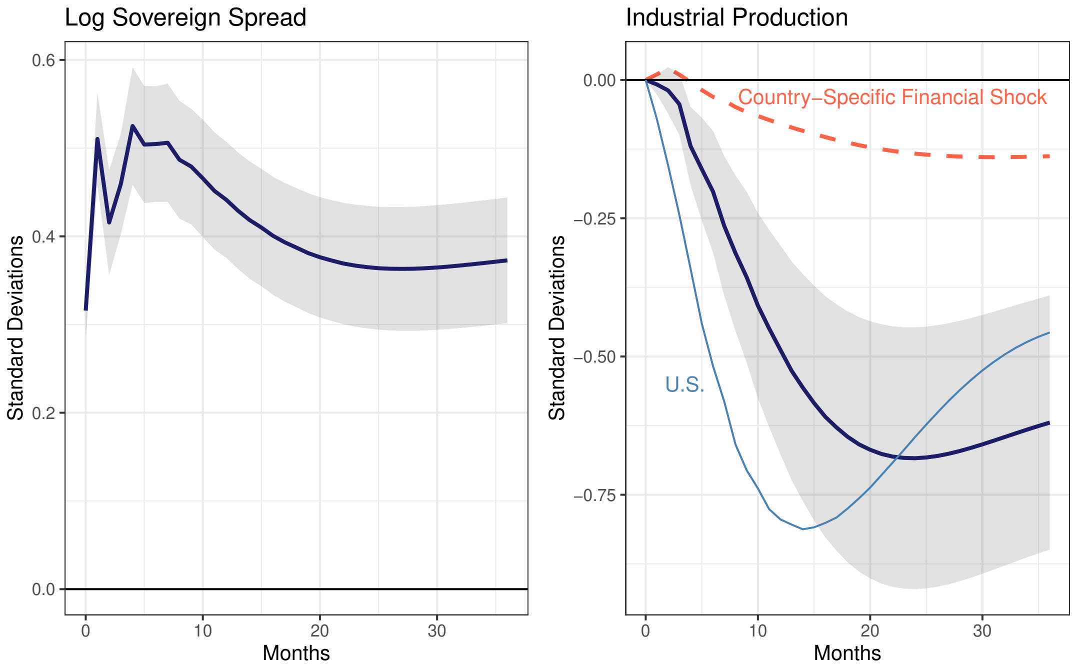
3.2 The average response to a global flight-to-safety shock

I first estimate the model with the global FTS shock, FTS_t and examine the average dynamics of economic activity and sovereign risk across EMs.

Figure 6 traces the average, or MG estimate impulse response of both logged sovereign spreads and IP growth to a 1-standard deviation FTS_t shock. Sovereign spreads react strongly and the response is front-loaded, displaying over-shooting behavior in the first few months following the shock. Economic activity significantly contracts over about 18 months. All units are measured in standard deviations to correct for heteroscedasticity across countries. For the sake of interpretation, the 18-month cumulative response in IP growth is approximately equivalent to a 4% contraction. For comparison I also show that U.S. economic activity (thin solid line) significantly contracts with a lag following an FTS shock, reflecting their global nature. The total U.S. contraction and recovery occurs faster and more sharply. The dashed line indicates the response of economic activity to a 1-standard deviation idiosyncratic country spread shock. As a proxy for country-specific financial shocks, the results indicate that global shocks are *much* more potent than their local counterparts.

[12]See for example Dees et al. [2007], Chudik et al. [2017], Hernandez-Vega [2019], Cesa-Bianchi et al. [2020].

Figure 6: Emerging Markets: Average Response to a 1-Standard Deviation FTS Shock (Solid), Response to a Country-Specific Sovereign Spread Shock (Dashed)



Cumulative MG Response (Equation 10) to a 1-standard deviation structural flight-to-safety shock, FTS_t (solid), and after controlling for contemporaneous VIX innovations (dashed). 95% non-parametric dispersion bands as computed in Equation 12. Log sovereign spread in monthly changes. Industrial production as year-over-year log change. Thin line in RHS figure is the IRF of U.S. national economic activity.

Both the response in sovereign spreads and the subsequent contraction in IP growth remain significant after orthogonalizing the FTS shock against changes in the VIX index, suggesting a distinct role for FTS shocks in shaping macroeconomic dynamics (Figure A.6. Figure A.7 shows that these results are robust to an FTS index identified under a more conservative flight-to-safety condition of $c = 1$, where both direction of asset price moves and also size are taken into account.

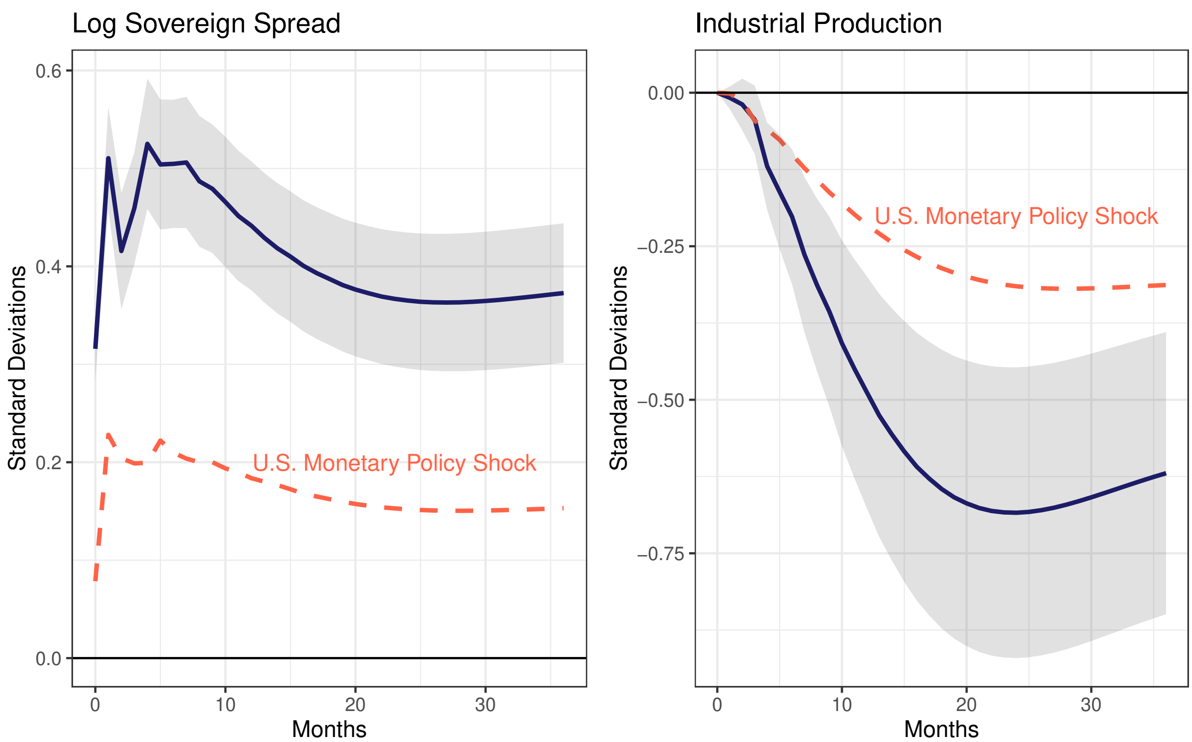
3.3 Comparing flights-to-safety and U.S. monetary policy shocks

To quantify the relative importance of global FTS shocks to other global financial shocks, I compare emerging market dynamics following a contractionary U.S. monetary policy shock. Both flights-to-safety and U.S. monetary policy lead to tighter global financial conditions, but the two shocks fundamentally differ and are uncorrelated. Monetary policy shocks are unanticipated changes in the U.S. policy rate while FTS shocks reflect unpredictable economic tail events or news.

I use high-frequency (30-minute) changes in the 3-month Treasury futures contract around FOMC announcements to capture U.S. monetary shocks following Kuttner [2001] and Gertler and Karadi [2015]. These are then aggregated to the monthly frequency.

The correlation between FTS shocks and U.S. monetary policy shocks is statistically indistinguishable from zero (correlation of 0.10), and as expected, there is no lead-lag relationship between the two shock series. Figure 7 reports MG IRFs, after replacing the FTS shock series with U.S. monetary policy shocks in Equation 9.

Figure 7: Emerging Markets: Average Response to a 1-Standard Deviation Contractionary U.S. Monetary Policy Shock



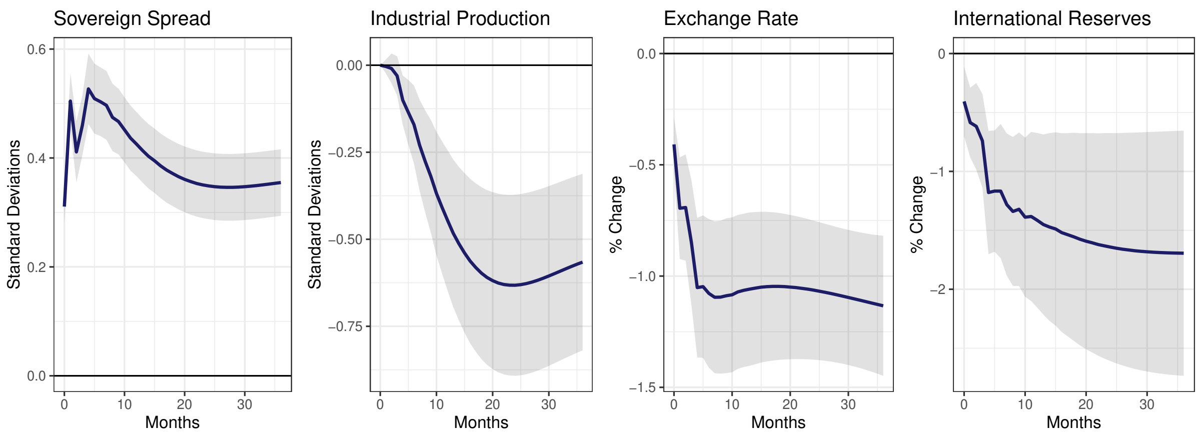
Cumulative MG Response (Equation 10) to a 1-standard deviation contractionary U.S. monetary policy shock. Monetary shocks are recovered from prices changes in the 3-month treasury futures contract within a 30-minute window of FOMC announcements. 95% non-parametric dispersion bands as computed in Equation 12. Log sovereign spread in monthly changes. Industrial production as year-over-year log change. Negative values imply exchange rate percent depreciation. International reserves in monthly log changes.

In response to a 1-standard deviation contractionary U.S. monetary shock, sovereign spreads widen and economic activity contracts – much like a flight-to-safety shock. A 1-standard deviation flight to safety elicits a response in sovereign spreads and economic activity roughly three and two times that of 1-standard deviation monetary policy shock, respectively. The standard deviation of the monetary policy shock series is equal to 3.54 basis points, while the standard deviation of changes in overall 3-month treasury yields over a similar period is 17.92 basis points. If we were to scale the monetary policy shocks up to have a similar standard deviation as the nominal 3-month yield, then the impact of a 1-standard deviation FTS shock on emerging markets would be roughly equal to the effects from a contraction of U.S. monetary policy between +36 and +48 basis points. This could alternatively be interpreted as the extent of monetary accommodation required to offset the impact of the average global flight-to-safety on emerging markets.

3.4 Incorporating exchange market pressure

Exchange market pressure (EMP), introduced early on in Girton and Roper [1977] along with its many variants (Hossfeld and Pramor [2018]), is a useful gauge of international pressure on the exchange rate either resisted through foreign exchange intervention or relieved through currency depreciation. EMP severity tends to capture periods of large, volatile capital inflows or outflows - often straining exchange rates and financial liquidity. Many recent studies highlight the role of global shocks in driving pressure on international markets via exchange or capital flow pressures across EMs.[13]

Figure 8: Emerging Markets: Average Response to a 1-Standard Deviation FTS Shock (Solid) and After Controlling for Changes in Logged VIX (Dashed)



Cumulative MG Response (Equation 10) to a 1-standard deviation structural flight-to-safety shock, FTS_t before (solid) and after controlling for contemporaneous VIX innovations (dashed). 95% non-parametric dispersion bands as computed in Equation 12. Log sovereign spread in monthly changes. Industrial production as year-over-year log change. Negative values imply exchange rate percent depreciation. International reserves in monthly log changes.

To consider the implications of EMP in the presence of global flights-to-safety, I augment the multi-country VAR with two additional country-specific endogenous variables: logged changes in USD exchange rates and international reserves. Global flight-to-safety shocks likely bear implications for EMP and its interaction with economic activity. Currency mismatch, for example, is a mechanism through which EMP may impact the real economy, as exchange rate depreciation increases the cost of foreign-denominated liabilities (Eichengreen and Hausmann [1999], Hofmann et al. [2019], Carstens and Shin [2019].). Known as the financial channel of exchange rates, the pecuniary externality caused by currency depreciation in the presence of currency mismatch offsets the classical trade channel where depreciation is considered stimulative. For this reason I focus on USD exchange rates given the recent evidence on the overwhelming role of the U.S.

[13] Fratzscher [2012], Aizenman and Binici [2016], Goldberg and Krogstrup [2018].

Dollar in the international monetary and price system.[14]

Figure 8 traces the Mean Group IRF from a 1-SD FTS shock from the model including exchange rates and international reserves. In addition to sovereign spreads widening and economic activity contracting, there is significant exchange market pressure across emerging markets. EMP manifests as both currencies rapidly depreciating against the USD and significant running down of international reserves. Within the first few months, exchange rates depreciate on average of 1.1%. After 10 months, reserves growth drops almost 1.5%. Both of these effects remain significant after orthogonalizing FTS shocks against the VIX index (Figure A.6) and when setting the FTS condition threshold to $c = 1$.

In section S2 of the Online Supplement I estimate the baseline results shown in Figure 8 using the Local Projection method of Jordà [2005] rather than the SVAR approach as a robustness check. The results remain consistent and significant regardless of modelling procedure. I also explore asymmetries, where positive (risk-off) and negative (risk-on) FTS shocks are allowed to impact emerging market dynamics differently, finding that after allowing for asymmetries, risk-off (positive FTS) shocks have substantially larger absolute effects compared to risk-on (negative FTS) shocks. This implies that the IRFs from the baseline symmetric VAR understate the macroeconomic and financial impact of adverse flights-to-safety.

4 Global Flight-to-Safety and Cross-Country Heterogeneity

Emerging Markets, on average, are subject to significant adjustments in response to a global flight-to-safety yet these effects may vary widely at the individual country level. An issue worth exploring then is whether these cross-country heterogeneities are large, and systematically linked. Specifically, financial market responses (sovereign spreads, exchange rates, international reserves) are relatively immediate compared to the adjustment of macroeconomic activity. This section uses cross-country heterogeneity to explore particular transmission channels moderating the impact of global FTS shocks on emerging market business cycles.

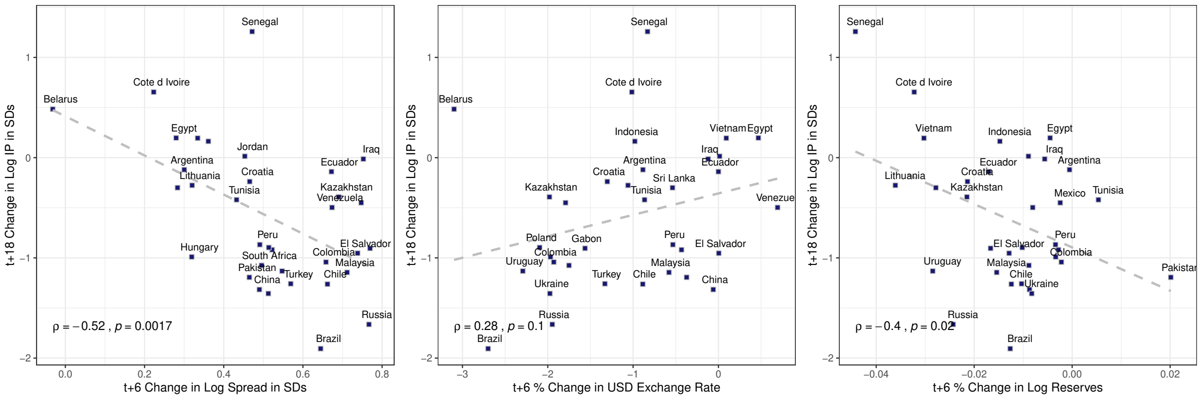
4.1 Shedding light on the financial transmission channels

Explicit identification of transmission channels at the international macro level remains a challenge. Generally speaking, there are two main approaches. The first is to develop a structural model while the second is a reduced form approach. An example of the

[14]The majority of trade is invoiced in USD, most countries peg to the USD, most international reserves are held in USD, most international financing is denominated in USD.

reduced form approach is taken in Akinci [2013] when attempting to quantify whether or not global financial shocks transmit to the real economy through their effect on domestic financial conditions. A basic counterfactual exercise is done by comparing the variance decomposition of a financial shock to real economic activity under the baseline VAR, to the same variance decomposition after shutting down effect of global financial shocks on domestic sovereign spreads (i.e. setting the coefficients in the sovereign spread equations associated with global financial shocks equal to zero). The results suggest that indeed, global shocks are amplified through their effect on sovereign spreads. However, the author also notes that this counterfactual exercise is subject to the Lucas Critique, as it is questionable whether all other coefficients characterizing the system would in fact stay constant when setting one particular coefficient to zero.

Figure 9: Heterogeneous Impact of Global FTS Shocks: 6-month Change in Sovereign Spreads (LHS), USD Exchange Rates (Center), International Reserves (RHS) vs. 18-Month Change in Economic Activity



Cumulative Responses (in standard deviations) to a 1-standard deviation structural flight-to-safety (FTS) shock, FTS_t (Equation 9).

Given the heterogeneity provided by my modeling approach, I extend upon the approach of Akinci [2013] by exploiting cross-country differences to infer potential transmission channels. By comparing countries with differential responses to FTS shocks, we can shed light on transmission mechanisms without imposing such controversial restrictions on the counterfactual estimation. For example, I investigate whether the impact of FTS shocks on economic activity is significantly stronger for the subset of countries where FTS shocks also impact severely sovereign spreads.

Figure 9 LHS shows across the 34 countries in the panel, the 6-month cumulative change in the log sovereign spread against the 18-month cumulative change in industrial production induced by a 1-SD FTS shock. The LHS correlation coefficient equals -0.52 and is statistically significant. Countries which realize wider short-run sovereign spread adjustment in response to an FTS shock are subject to deeper long-run economic contractions. While Akinci [2013] finds that transmission of global financial shocks through country spreads account for two-thirds of the impact on macroeconomic activity, I find that the role of tightened country spreads explain closer to 27% of the variation in macroeconomic adjustment.

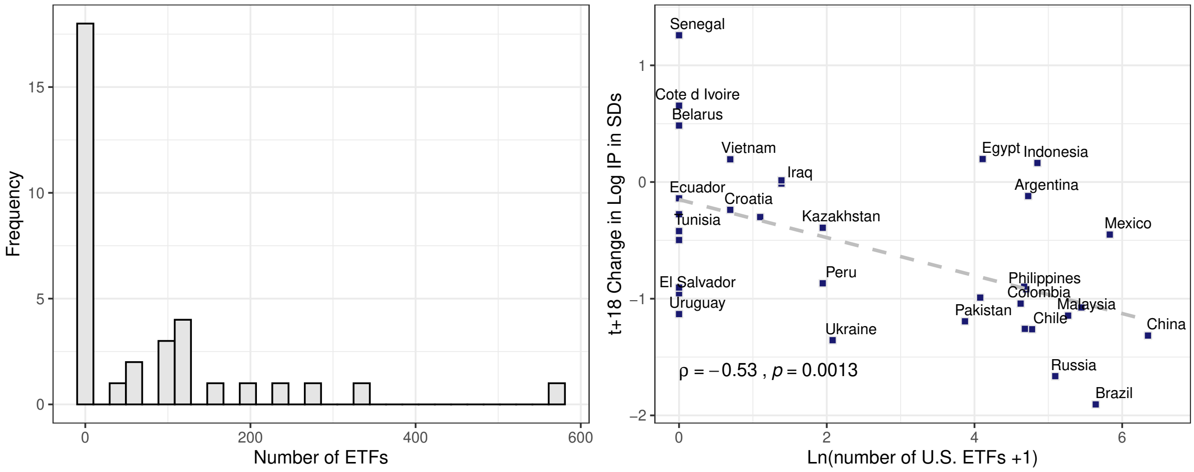
Similarly, the center figure shows that countries which experience greater currency depreciation vis-a-vis the USD amid an FTS shock also realize larger subsequent IP contractions. By contrast,the RHS figure shows that countries which more aggressively expend reserves also realize shallower subsequent contractions in industrial production (correlation equal to -0.40). Taken together, these associations suggest that the impact of FTS shocks on the real economy are partly determined by the sensitivity of domestic financial factors along with the intensity of policy responses.

4.2 U.S. Integration: Do ETFs amplify the impact of Flight-to-Safety shocks?

The extent to which FTS shocks eventually impact economic activity in emerging markets suggestively depend on the sensitivity to domestic financial factors – response of domestic financial conditions and the policy response with international reserves – as shown. Additionally, financial openness or integration with advanced economies may be a critical factor which also shapes the business cycle response to foreign financial shocks. In this context, the advent of exchange-traded funds (ETFs) in advanced economies has been of growing interest, giving global investors considerable access EM investments with the promise of superior liquidity. With them comes the potential for much greater capital flow volatility. In recent work, Converse et al. [2020] document that equity and bond ETF flows are significantly more sensitive to global financial conditions than mutual fund flows, amplyfing the global financial cycle in emerging markets.

To capture the role of financial integration with the U.S. through ETFs, I investigate whether the impact of FTS shocks differ systematically in countries which have either equity or bond ETFs available for trade on U.S. exchanges compared to those which do not (or have very few). The former countries, by virtue of selection, are likely to have more advanced financial markets and more open capital accounts – not just with the United States. Greater financial development implies that these countries enjoy lower financing costs on average. At the same time, these countries may be particularly sensitive to flight-to-safety shocks and associated sudden capital outflows as global investors withdraw capital from emerging markets, deemed relatively risky investments. Meanwhile, Converse et al. [2020] argue that ETFs may attract different investors than mutual funds, specifically those which put greater value on liquidity, and do not put as much value on local fundamentals when allocating capital. This ETF-specific channel can amplify the impact of external shocks even conditional on financial openness. Table S.4 provides the number of U.S. traded ETFs granting exposure to each country in the sample as of

Figure 10: Distribution of the number of ETFs traded on U.S. exchanges each EM has presence within



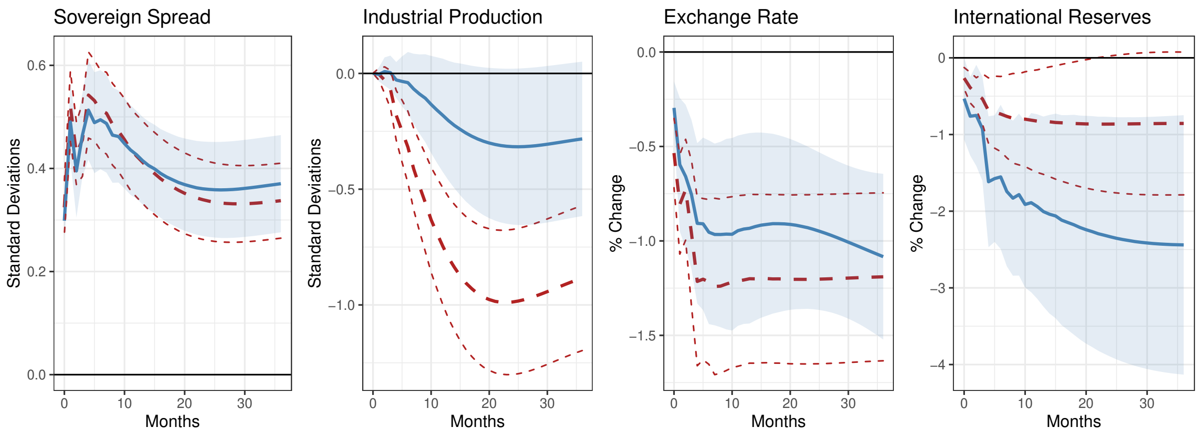
LHS: Frequency distribution of the number of U.S. ETFs a country has presence within (as of October 2020). Source: etfdb.com. RHS: x-axis plots the ln(number of U.S. ETFs +1) against the 18-month cumulative IP growth response to a 1-SD FTS shock.

October 2020. Brazil, China, Mexico and South Africa each have more than 200 U.S. traded ETFs which at least some financial assets based in those countries. By contrast, several countries have little or no investment through U.S. ETF holdings: Belarus, Cote d'Ivoire, Croatia, Ecuador, Vietnam, among others. A clear demarcation is observed between Ukraine, which a U.S. investor can gain exposure through 7 ETFs and the next country Pakistan, for which the number of ETFs jump to 47.

Figure 10 shows the frequency distribution (LHS) of countries by number of U.S. based ETFs. Roughly half of the countries have little or no ETF presence in the United States. On the RHS, the relationship between the logged number of ETFs per country on the x-axis and the response of IP growth to a FTS shock is plotted. It's quite clear from a cursory look that economic contractions induced bye global FTS shocks are deeper in countries with greater presence among U.S. ETFs.

Figure 11 traces the IRFs to a 1-SD FTS shock for two different groups of EMs. The dashed line refers to countries with a substantial presence in the U.S. ETF space (Argentina, Brazil, Chile, China, Colombia, Egypt, Hungary, Indonesia, Malaysia, Mexico, Pakistan, Philippines, Poland, Russia, South Africa, and Turkey). The solid line is the MG IRF for countries with little to no ETF presence (Belarus, Cote d'Ivoire, Croatia, Ecuador, El Salvador, Gabon, Iraq, Jordan, Kazakhstan, Lithuania, Peru, Senegal, Sri Lanka, Tunisia, Ukraine, Uruguay, Venezuela, and Vietnam). The minimum number of ETFs available among the countries with substantial presence is 47 (Pakistan) and the max is China (571). The minimum for the group with low ETF presence is zero (Belarus, Cote d'Ivoire, Ecuador, Gabon, Lithuania, Senegal, Tunisia, Uruguay, Venezuela) and the maximum is Ukraine with 7 ETFs.

Figure 11: Average Response to a 1-Standard Deviation FTS Shock for Countries with U.S. ETF presence (dashed) and those without (solid)



Cumulative MG response (Equation 10) to a 1-standard deviation structural flight-to-safety shock, FTS_t. 95% dispersion bands as computed in Equation 12. Log sovereign spread in monthly changes. Industrial production as year-over-year log change. Negative exchange rate response equals percent depreciation against the USD. International Reserves as log monthly change. Countries with U.S. ETF presence: Argentina, Brazil, Chile, China, Colombia, Egypt, Hungary, Indonesia, Malaysia, Mexico, Pakistan, Philippines, Poland, Russia South Africa, Turkey.

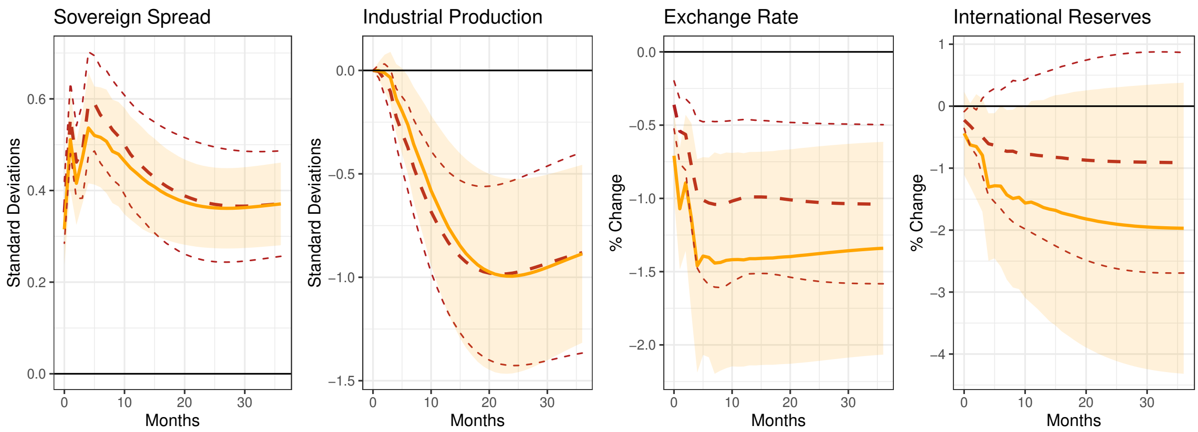
Despite similar responses in sovereign spreads to a global FTS shock, The group of countries with heavy ETF presence are subject to significantly deeper – roughly four times deeper – economic contractions than the group without U.S. ETF presence. While both groups of countries experience heavy exchange market pressure following a global FTS shock, the groups differ by whether the pressure is relieved through currency depreciation or expending reserves. Countries with heavy ETF presence realize relatively sharper currency depreciation while expending relatively less international reserves, with the reverse holding for the group without an ETF presence.

Controlling for Financial Openness

Countries with significant ETF presence on developed market exchanges may simply be more financial integrated and developed with other countries other than the U.S., and thereby more sensitive to global financial shocks. To test whether the ETF differential is soley proxying for broad financial openness, I take the 16 EMs with high ETF presence and re-sort these countries into those with high versus low capital inflow controls. Data on capital inflow controls are taken from the Fernández et al. [2016] data set, and I arrive at country-specific values by averaging values of aggregate capital inflow control index from 2000-2019 for each country.[15] Splitting the ETF EMs into two equal-sized groups, the countries with ETF presence but high or above-median capital controls are: China,

[15] Of the 34 EMs in the sample, 27 have capital control data available.

Figure 12: Average Response to a 1-Standard Deviation FTS Shock for Countries with U.S. ETF presence, sorted into High (Dashed) and Low (Solid) Capital Inflow Controls



Cumulative MG response (Equation 10) to a 1-standard deviation structural flight-to-safety shock, FTS_t. 95% dispersion bands as computed in Equation 12. Log sovereign spread in monthly changes. Industrial production as year-over-year log change. Negative exchange rate response equals percent depreciation against the USD. International Reserves as log monthly change. Countries with U.S. ETF presence and low capital controls: Argentina, Brazil, Chile, Egypt, Hungary, Poland, South Africa, Turkey. Countries with U.S. ETF presence and high capital controls: China, Colombia, Indonesia, Malaysia, Mexico, Pakistan, Philippines, Russia.

Colombia, Indonesia, Malaysia, Mexico, Pakistan, Philippines, Russia. The countries with ETF presence but low or below-median capital inflow controls are: Argentina, Brazil, Chile, Egypt, Hungary, Poland, South Africa, Turkey. The idea here is that if general financial openness matters, then there should be a differential impact of FTS shocks observed based on financial openness even after conditioning on high ETF intensity.

Figure 12 traces MG impulse response functions for these two groups of ETF-intensive EMs. It becomes immediately clear that financial openness is generally not driving the strong impact of global FTS shocks on EM economic activity with high ETF presence. The response of sovereign spreads and industrial production between these two sub groups are statistically indistinguishable. Although note that this doesn't mean that capital controls are ineffective: Those countries with stricter capital flow controls do experience less exchange market pressure (both as less exchange depreciation and reserves depletion) amid global flights-to-safety. This evidence corroborates Converse et al. [2020] in that the growth of ETFs poses a potential amplification mechanism for the transmission of global shocks, and the channel may not simply be due to financial openness, but the unique integration with the U.S. or liquidity-preferring behavior of ETF investors.

4.3 Explaining cross-country macroeconomic adjustment to flights to safety

Taking stock of the systematic heterogeneity between domestic financial factors and the transmission of global shocks, The evidence presented thus far suggests that a global FTS shock can induce deeper subsequent contractions in industrial production when the early response in sovereign spreads are sharper, when the exchange rate depreciates more, or when there is greater U.S. ETF presence. Meanwhile, actively running down international reserves in response to an FTS shock is associated with a buffering effect on economic activity. These domestic financial factors may interact with each other, or possibly explain the same underlying financial exposure. To analyze the joint influence of these financial factors on the long-run impact of FTS shocks on economic activity, I propose the following cross-sectional regression:

$$E_i[\Delta y_{i,t,t+18}|FTS_t] = \alpha + \beta_1 E_i[\Delta s_{i,t,t+6}|FTS_t] + \beta_2 E_i[\Delta fx_{i,t,t+6}|FTS_t] + \beta_3 E_i[\Delta res_{i,t,t+6}|FTS_t] + \beta_4 \ln(ETF_i + 1) + \beta_5 X_i + e_i, \quad (13)$$

where the dependent variable $E_i[\Delta y_{i,t,t+18}|FTS_t]$ is country i's cumulative response in IP growth to a 1-SD FTS shock after 18 months. $E_i[\Delta s_{i,t,t+6}|FTS_t]$, $E_i[\Delta fx_{i,t,t+6}|FTS_t]$, and $E_i[\Delta res_{i,t,t+6}|FTS_t]$ are the 6-month cumulative response of country i's sovereign spread, USD exchange rate, and international reserves to a 1-SD FTS shock, respectively. Finally ETF_i is the number of U.S. traded ETF's country i maintains a presence within and X_i refers to additional controls. Specifically, I include an indicator denoting whether the country is a commodity exporter to capture economic composition.[16] Standard errors are robust to heteroscedasticity. Both the dependent variable and the independent variables are estimates, thus subject to measurement error. In the case of uncorrelated measurement error, attenuation will bias the coefficients estimated by least squares towards zero. Therefore, a most plausible scenario is one where the standard errors are biased upwards and the point estimates are biased downwards, so estimated associations from Equation 13 would understate the true association strength.

Table A.4 reports the regression results from estimating Equation 13. Deeper subsequent IP growth contractions are associated with countries which initially realize wider sovereign spreads or currency depreciation in response to a FTS shock. Countries which expend more reserves as a buffer against an FTS shock realize economic contractions which are comparatively smaller. Moreover, having a larger presence in the U.S. ETF in-

[16] Commodity exporter is defined as in Aslam et al. [2016], a country with greater than 35% of exports in commodities and greater than 5% of all trade in commodities, on average over 1960-2014. These countries are: Argentina, Brazil, Chile, Colombia, Cote d' Ivoire, Ecuador, Gabon, Indonesia, Iraq, Kazakhstan, Malaysia, Peru, Russia, Uruguay, Venezuela.

vestable space is associated with deeper economic contractions following flights-to-safety, and this relationship is significant and robust.

To consider the interaction of international reserves and exchange rate movements which together characterize total exchange market pressure, I include the interaction term, $E_i[\Delta fx_{i,t,t+6}|FTS_t] \times E_i[\Delta res_{i,t,t+6}|FTS_t]$, which is abbreviated in the table for succinctness. The interaction term is highly significant and negative, while the marginal effect of exchange rate depreciation is insignificant,and the marginal effect of expending reserves remains highly significant. Therefore a possible interpretation of the three estimates is that expending reserves (i.e. leaning against the wind) buffers against the real economic impact following a global FTS shock, and this effect weakens with greater coincident exchange rate depreciation. In other words, following a global FTS shock, the buffering effects of expending reserves on subsequent economic growth appears most effective when the exchange rate is successfully stabilized. Column 6 shows that results persist after controlling for commodity intensity to capture differences in economic structure across countries.

Taken together, these domestic financial factors explain up to 60% of the cross-country variance in the macroeconomic sensitivity to a global FTS shock. Moreover, the results suggest ample evidence that these financial heterogeneities are not simply confounded with one another, rather they explain distinct cross-country variation in the macroeconomic adjustment to FTS shocks. Tables A.5 and A.6 replicate the regression results after replacing FTS shocks with the VIX or Global Financial Cycle in the multi-country VAR (Equation 9) for robustness. The significance of most financial factors disappear, and the explanatory power of the regression drops substantially (adjusted R^2 falls from 60% to between 40%-50%). One possible reason for this is that FTS shocks are more cleanly identifying a specific financial shock which transmits to real economic activity via the reported margins of heterogeneity. Fluctuations in the global financial cycle and the VIX index of course account for shocks that generate flights-to-safety, but also many other types of adverse shocks. If these other shocks transmit via other margins of heterogeneity, we'd see a similar sort of attenuation in the results as we moved from FTS shocks to the VIX or global financial cycle variable. All three measures of global financial stress highlight a significant role of ETF intensity and exchange market pressure in explaining cross-country macroeconomic adjustment to a global FTS shock.

5 Concluding Remarks

This paper presents a new measure of global financial shocks specifically reflecting flight-to-safety to test their impact on domestic financial and economic conditions in emerging markets. The largest daily FTS shocks do not correspond with the largest stock market crashes nor a majority of the largest jumps in the VIX index. Flight-to-safety shocks do map to economically disruptive historical events, informing current and future changes in interest rates, exchange rates, commodities, inflation expectations, the U.S. Dollar, and contain both components reflecting shifting risk sentiment and global demand. In Section S3 of the Online Supplement, I further investigate the separation of FTS shocks into excess risk sentiment and global demand components.

I investigate how global FTS shocks shape macroeconomic dynamics in the U.S. and a panel of 34 emerging markets within a multi-country VAR framework. In response to a global FTS shock, sovereign spreads widen dramatically, exchange market pressure increases and economic activity subsequently contracts in both emerging markets and the U.S. over a period of 18 months. These effects persist when using variation in FTS shocks that is uncorrelated with the VIX index.

I further show that there is significant country-specific heterogeneity in the impact of FTS shocks across EMs. Countries realizing sharper adjustment in their sovereign spreads and greater currency depreciation are subject to deeper subsequent economic contractions. Meanwhile, countries which aggressively expend international reserves, leaning against the wind in response to an FTS shock, are subject to smaller subsequent economic contractions, especially when the exchange rate is successfully stabilized. Moreover, the impact of FTS shocks on economic growth is significantly amplified among countries with substantial presence within U.S. traded ETFs. These features are supportive of a broad range of risk-centric macroeconomic models where shocks to risk premia propagate through the real economy, and policy intervention can mitigate these effects.

The role of domestic financial factors moderating the pass-through of global shocks to local economic conditions coincides with the findings of Akinci [2013], Aizenman et al. [2016] and Kalemli-Ozcan [2019] and recent risk-centric theoretical frameworks of Caballero and Simsek [2020b], Caballero and Simsek [2020c], Jeanne and Sandri [2020] and Davis et al. [2020]. Along the international dimension, the buffering effects of running down international reserves suggest an important role for monetary policies to serve as macroprudential policy-puts, buffering against external tail shocks in a financially integrated world. The amplification mechanism of global shocks through highly volatile investment flows, particularly through ETFs and financial integration with the U.S., also warrants further research given the rapidly expanding footprint of the industry.

References

R. Ahmed. Commodity currencies and causality: Some high-frequency evidence. *Economics Letters*, 189:109016, 2020.

R. Ahmed. Monetary policy spillovers under intermediate exchange rate regimes. *Journal of International Money and Finance*, 112:102342, 2021.

J. Aizenman and M. Binici. Exchange market pressure in OECD and emerging economies: Domestic vs. external factors and capital flows in the old and new normal. *Journal of International Money and Finance*, 66(C):65–87, 2016. doi: 10.1016/j.jimonfin.2015.1. URL https://ideas.repec.org/a/eee/jimfin/v66y2016icp65-87.html.

J. Aizenman and J. Lee. International reserves: precautionary versus mercantilist views, theory and evidence. *Open Economies Review*, 18(2):191–214, 2007.

J. Aizenman, M. D. Chinn, and H. Ito. Monetary policy spillovers and the trilemma in the new normal: Periphery country sensitivity to core country conditions. *Journal of International Money and Finance*, 68:298 – 330, 2016. ISSN 0261-5606. doi: https://doi.org/10.1016/j.jimonfin.2016.02.008. URL http://www.sciencedirect.com/science/article/pii/S0261560616000322.

O. Akinci. Global financial conditions, country spreads and macroeconomic fluctuations in emerging countries. *Journal of International Economics*, 91(2):358 – 371, 2013. ISSN 0022-1996. doi: https://doi.org/10.1016/j.jinteco.2013.07.005. URL http://www.sciencedirect.com/science/article/pii/S0022199613000743.

R. Alquist, S. Bhattarai, and O. Coibion. Commodity-price comovement and global economic activity. *Journal of Monetary Economics*, 112:41–56, 2020.

A. Aslam, S. Beidas-Strom, R. Bems, O. Celasun, S. K. Çelik, and Z. Koczan. Trading on Their Terms? Commodity Exporters in the Aftermath of the Commodity Boom. IMF Working Papers 2016/027, International Monetary Fund, Feb. 2016. URL https://ideas.repec.org/p/imf/imfwpa/2016-027.html.

L. Baele, G. Bekaert, K. Inghelbrecht, and M. Wei. Flights to Safety. *The Review of Financial Studies*, 33(2):689–746, 06 2019. ISSN 0893-9454. doi: 10.1093/rfs/hhz055. URL https://doi.org/10.1093/rfs/hhz055.

W. Bailey and K. C. Chan. Macroeconomic influences and the variability of the commodity futures basis. *The Journal of Finance*, 48(2):555–573, 1993.

A. Beber, M. Brandt, and J. Cen. Switching Risk Off: FX Correlations and Risk Premia. CEPR Discussion Papers 10214, C.E.P.R. Discussion Papers, Oct. 2014. URL https://ideas.repec.org/p/cpr/ceprdp/10214.html.

B. S. Bernanke, M. Gertler, and S. Gilchrist. The financial accelerator in a quantitative business cycle framework. *Handbook of macroeconomics*, 1:1341–1393, 1999.

B. S. Bernanke, J. Boivin, and P. Eliasz. Measuring the effects of monetary policy: a factor-augmented vector autoregressive (favar) approach. *The Quarterly journal of economics*, 120(1):387–422, 2005.

N. Bloom. The impact of uncertainty shocks. *Econometrica*, 77(3):623–685, 2009.

T. Bollerslev. Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3):307 – 327, 1986. ISSN 0304-4076. doi: https://doi.org/10.1016/0304-4076(86)90063-1. URL http://www.sciencedirect.com/science/article/pii/0304407686900631.

J. Caballero, A. Fernández, and J. Park. On corporate borrowing, credit spreads and economic activity in emerging economies: An empirical investigation. *Journal of International Economics*, 118:160 – 178, 2019. ISSN 0022-1996. doi: https://doi.org/10.1016/j.jinteco.2018.11.010. URL http://www.sciencedirect.com/science/article/pii/S002219961830446X.

R. Caballero and G. Kamber. On the global Impact of risk-off shocks and policy-put frameworks. BIS Working Papers 772, Bank for International Settlements, Mar. 2019. URL https://ideas.repec.org/p/bis/biswps/772.html.

R. J. Caballero and A. Simsek. A risk-centric model of demand recessions and speculation. *The Quarterly Journal of Economics*, 135(3):1493–1566, 2020a.

R. J. Caballero and A. Simsek. A model of fickle capital flows and retrenchment. *Journal of Political Economy*, 128(6):2288–2328, 2020b.

R. J. Caballero and A. Simsek. A model of asset price spirals and aggregate demand amplification of a" covid-19" shock. Technical report, National Bureau of Economic Research, 2020c.

A. Carstens and H. S. Shin. Emerging markets aren't out of the woods yet. *Foreign Affairs*, 2019.

A. Cesa-Bianchi, M. H. Pesaran, and A. Rebucci. Uncertainty and economic activity: A multicountry perspective. *The Review of Financial Studies*, 33(8):3393–3445, 2020.

A. Chari, K. D. Stedman, and C. Lundblad. Capital flows in risky times: Risk-on/risk-off and emerging market tail risk. Working Paper 27927, National Bureau of Economic Research, October 2020. URL http://www.nber.org/papers/w27927.

A. Chudik and M. H. Pesaran. Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. *Journal of Econometrics*, 188(2):393–420, 2015. doi: 10.1016/j.jeconom.2015.03. URL https://ideas.repec.org/a/eee/econom/v188y2015i2p393-420.html.

A. Chudik and M. H. Pesaran. Theory and practice of gvar modelling. *Journal of Economic Surveys*, 30(1):165–197, 2016.

A. Chudik and M. H. Pesaran. Mean group estimation in presence of weakly cross-correlated estimators. *Economics Letters*, 175:101 – 105, 2019. ISSN 0165-1765. doi: https://doi.org/10.1016/j.econlet.2018.12.036. URL http://www.sciencedirect.com/science/article/pii/S0165176518305305.

A. Chudik, K. Mohaddes, M. H. Pesaran, and M. Raissi. Is There a Debt-Threshold Effect on Output Growth? *The Review of Economics and Statistics*, 99(1):135–150, March 2017. URL https://ideas.repec.org/a/tpr/restat/v99y2017i1p135-150.html.

A. Chudik, K. Mohaddes, M. H. Pesaran, M. Raissi, and A. Rebucci. A counterfactual economic analysis of covid-19 using a threshold augmented multi-country model. Working Paper 27855, National Bureau of Economic Research, September 2020. URL http://www.nber.org/papers/w27855.

N. Converse, E. L. Yeyati, and T. Williams. How ETFs Amplify the Global Financial Cycle in Emerging Markets. International Finance Discussion Papers 1268, Board of Governors of the Federal Reserve System (U.S.), Jan. 2020. URL https://ideas.repec.org/p/fip/fedgif/1268.html.

D. Datta, J. M. Londono, B. Sun, D. O. Beltran, T. RT Ferreira, M. M. Iacoviello, M. R. Jahan-Parvar, C. Li, M. Rodriguez, and J. H. Rogers. Taxonomy of global risk, uncertainty, and volatility measures. *Matteo M. and Jahan-Parvar, Mohammad R. and Li, Canlin and Rodriguez, Marius and Rogers, John H., Taxonomy of Global Risk, Uncertainty, and Volatility Measures (2017-11-21). FRB International Finance Discussion Paper*, (1216), 2017.

J. S. Davis, M. B. Devereux, and C. Yu. Sudden Stops and Optimal Foreign Exchange Intervention. NBER Working Papers 28079, National Bureau of Economic Research, Inc, Nov. 2020. URL https://ideas.repec.org/p/nbr/nberwo/28079.html.

R. De Bock and I. de Carvalho Filho. The behavior of currencies during risk-off episodes. *Journal of International Money and Finance*, 53(C):218–234, 2015a. doi: 10.1016/j.jimonfin.2014.1. URL https://ideas.repec.org/a/eee/jimfin/v53y2015icp218-234.html.

R. De Bock and I. de Carvalho Filho. The behavior of currencies during risk-off episodes. *Journal of International Money and Finance*, 53:218–234, 2015b.

S. Dees, S. Holly, M. H. Pesaran, and L. V. Smith. Long run macroeconomic relations in the global economy. *Economics: The Open-Access, Open-Assessment E-Journal*, 1(5): 1–29, 2007.

S. Delle Chiaie, L. Ferrara, and D. Giannone. Common factors of commodity prices. *Research Bulletin*, 51, 2018. URL https://ideas.repec.org/a/ecb/ecbrbu/20180051.html.

K. M. Dominguez, Y. Hashimoto, and T. Ito. International reserves and the global financial crisis. *Journal of International Economics*, 88(2):388–406, 2012.

G. Duncombe, M. Nigro, and B. Kay. Forecasting factor returns. *Two Sigma Investments*, 2018.

K. Dusak. Futures trading and investor returns: An investigation of commodity market risk premiums. *Journal of Political economy*, 81(6):1387–1406, 1973.

B. Eichengreen and R. Hausmann. Exchange rates and financial fragility. Technical report, National bureau of economic research, 1999.

R. Engle. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, 20(3):339–350, 2002.

C. B. Erb and C. R. Harvey. The strategic and tactical value of commodity futures. *Financial Analysts Journal*, 62(2):69–97, 2006.

E. F. Fama and K. R. French. Business cycles and the behavior of metals prices. *The Journal of Finance*, 43(5):1075–1093, 1988.

B. Feldman and H. Till. Backwardation and commodity futures performance: Evidence from evolving agricultural markets. *The Journal of Alternative Investments*, 9(3):24–39, 2006.

A. Fernandez, S. Schmitt-Grohe, and M. Uribe. World shocks, world prices, and business cycles: An empirical investigation. *Journal of International Economics*, 108:S2–S14, 2017.

A. Fernández, M. W. Klein, A. Rebucci, M. Schindler, and M. Uribe. Capital Control Measures: A New Dataset. *IMF Economic Review*, 64(3):548–574, August 2016. doi: 10.1057/imfer.2016.11. URL https://ideas.repec.org/a/pal/imfecr/v64y2016i3d10.1057_imfer.2016.11.html.

M. Fratzscher. Capital flows, push versus pull factors and the global financial crisis. *Journal of International Economics*, 88(2):341 – 356, 2012. ISSN 0022-1996. doi: https://doi.org/10.1016/j.jinteco.2012.05.003. URL http://www.sciencedirect.com/science/article/pii/S0022199612000931. NBER Global.

M. Gertler and P. Karadi. Monetary policy surprises, credit costs, and economic activity. *American Economic Journal: Macroeconomics*, 7(1):44–76, 2015.

A. R. Ghosh, J. D. Ostry, and M. S. Qureshi. When do capital inflow surges end in tears? *American Economic Review*, 106(5):581–85, 2016.

L. Girton and D. Roper. A monetary model of exchange market pressure applied to the postwar canadian experience. *The American Economic Review*, 67(4):537–548, 1977.

L. R. Glosten, R. Jagannathan, and D. E. Runkle. On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. *Journal of Finance*, 48(5):1779–1801, December 1993. URL https://ideas.repec.org/a/bla/jfinan/v48y1993i5p1779-1801.html.

L. S. Goldberg and S. Krogstrup. International Capital Flow Pressures. NBER Working Papers 24286, National Bureau of Economic Research, Inc, Feb. 2018. URL https://ideas.repec.org/p/nbr/nberwo/24286.html.

G. Gorton and K. G. Rouwenhorst. Facts and fantasies about commodity futures. *Financial Analysts Journal*, 62(2):47–68, 2006.

G. B. Gorton, F. Hayashi, and K. G. Rouwenhorst. The fundamentals of commodity futures returns. *Review of Finance*, 17(1):35–105, 2013.

J. Haubrich, G. Pennacchi, and P. Ritchken. Inflation expectations, real rates, and risk premia: Evidence from inflation swaps. *The Review of Financial Studies*, 25(5):1588–1629, 2012.

M. Hernandez-Vega. Estimating Capital Flows To Emerging Market Economies With Heterogeneous Panels. *Macroeconomic Dynamics*, 23(5):2068–2088, July 2019. URL https://ideas.repec.org/a/cup/macdyn/v23y2019i05p2068-2088_00.html.

D. Hirshleifer. Residual risk, trading costs, and commodity futures risk premia. *The Review of Financial Studies*, 1(2):173–193, 1988.

B. Hofmann, I. Shim, and H. S. Shin. Bond risk premia and the exchange rate. BIS Working Papers 775, Bank for International Settlements, Mar. 2019. URL https://ideas.repec.org/p/bis/biswps/775.html.

H. Hong and M. Yogo. What does futures market interest tell us about the macroeconomy and asset prices? *Journal of Financial Economics*, 105(3):473–490, 2012.

O. Hossfeld and M. Pramor. Global liquidity and exchange market pressure in emerging market economies. Technical report, 2018.

M. Jarociński and P. Karadi. Deconstructing monetary policy surprises—the role of information shocks. *American Economic Journal: Macroeconomics*, 12(2):1–43, 2020.

O. Jeanne and R. Ranciere. The optimal level of international reserves for emerging market countries: A new formula and some applications. *The Economic Journal*, 121 (555):905–930, 2011.

O. Jeanne and D. Sandri. Global financial cycle and liquidity management. Technical report, National Bureau of Economic Research, 2020.

Ò. Jordà. Estimation and inference of impulse responses by local projections. *American economic review*, 95(1):161–182, 2005.

S. Kalemli-Ozcan. U.S. Monetary Policy and International Risk Spillovers. NBER Working Papers 26297, National Bureau of Economic Research, Inc, Sept. 2019. URL https://ideas.repec.org/p/nbr/nberwo/26297.html.

L. Kilian. Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review*, 99(3):1053–69, 2009.

L. Kilian and X. Zhou. Modeling fluctuations in the global demand for commodities. *Journal of International Money and Finance*, 88:54–78, 2018.

O. Kucher and A. Kurov. Business cycle, storage, and energy prices. *Review of Financial Economics*, 23(4):217–226, 2014. doi: 10.1016/j.rfe.2014.09.001. URL https://ideas.repec.org/a/eee/revfin/v23y2014i4p217-226.html.

K. N. Kuttner. Monetary policy surprises and interest rates: Evidence from the fed funds futures market. *Journal of monetary economics*, 47(3):523–544, 2001.

E. G. Mendoza. Sudden stops, financial crises, and leverage. *American Economic Review*, 100(5):1941–66, 2010.

S. Miranda-Agrippino and H. Rey. U.S. Monetary Policy and the Global Financial Cycle. *The Review of Economic Studies*, 05 2020. ISSN 0034-6527. doi: 10.1093/restud/rdaa019. URL https://doi.org/10.1093/restud/rdaa019. rdaa019.

M. Obstfeld, J. D. Ostry, and M. S. Qureshi. A tie that binds: Revisiting the trilemma in emerging market economies. *Review of Economics and Statistics*, 101(2):279–293, 2019.

B. Pesaran and M. H. Pesaran. Conditional volatility and correlations of weekly returns and the var analysis of 2008 stock market crash. *Economic Modelling*, 27(6):1398–1416, 2010.

M. Pesaran and R. Smith. Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics*, 68(1):79 – 113, 1995. ISSN 0304-4076. doi: https://doi.org/10.1016/0304-4076(94)01644-F. URL http://www.sciencedirect.com/science/article/pii/030440769401644F.

M. H. Pesaran. Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica*, 74(4):967–1012, 2006. ISSN 00129682, 14680262. URL http://www.jstor.org/stable/3805914.

M. H. Pesaran, T. Schuermann, and S. M. Weiner. Modeling regional interdependencies using a global error-correcting macroeconometric model. *Journal of Business Economic Statistics*, 22(2):129–162, 2004. ISSN 07350015. URL http://www.jstor.org/stable/1392171.

H. Rey. Dilemma not Trilemma: The Global Financial Cycle and Monetary Policy Independence. NBER Working Papers 21162, National Bureau of Economic Research, Inc, May 2015. URL https://ideas.repec.org/p/nbr/nberwo/21162.html.

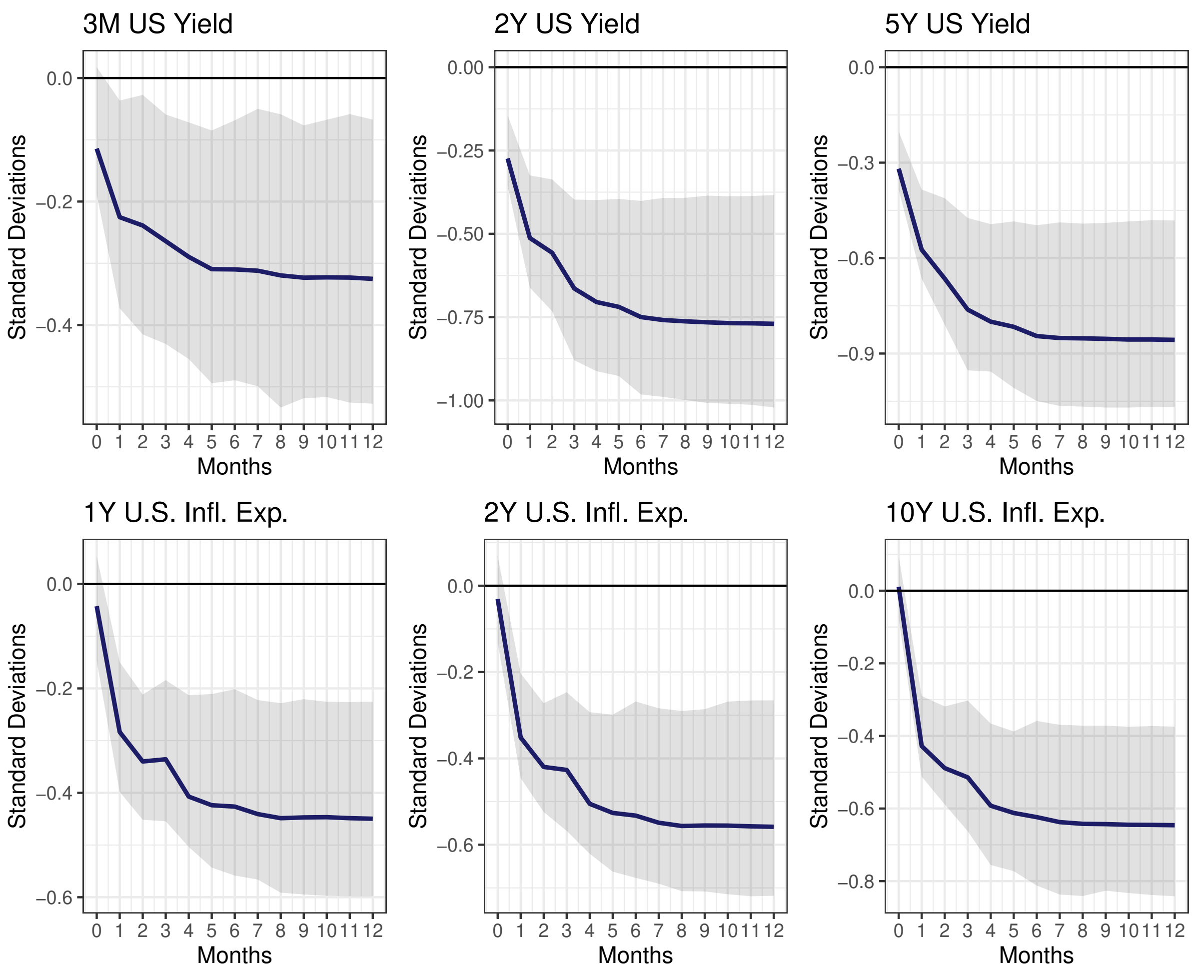
S. Shousha. Macroeconomic effects of commodity booms and busts: The role of financial frictions. 2016.

M. Szymanowska, F. De Roon, T. Nijman, and R. Van Den Goorbergh. An anatomy of commodity futures risk premia. *The Journal of Finance*, 69(1):453–482, 2014.

M. Uribe and V. Z. Yue. Country spreads and emerging countries: Who drives whom? *Journal of International Economics*, 69(1):6–36, June 2006. URL https://ideas.repec.org/a/eee/inecon/v69y2006i1p6-36.html.

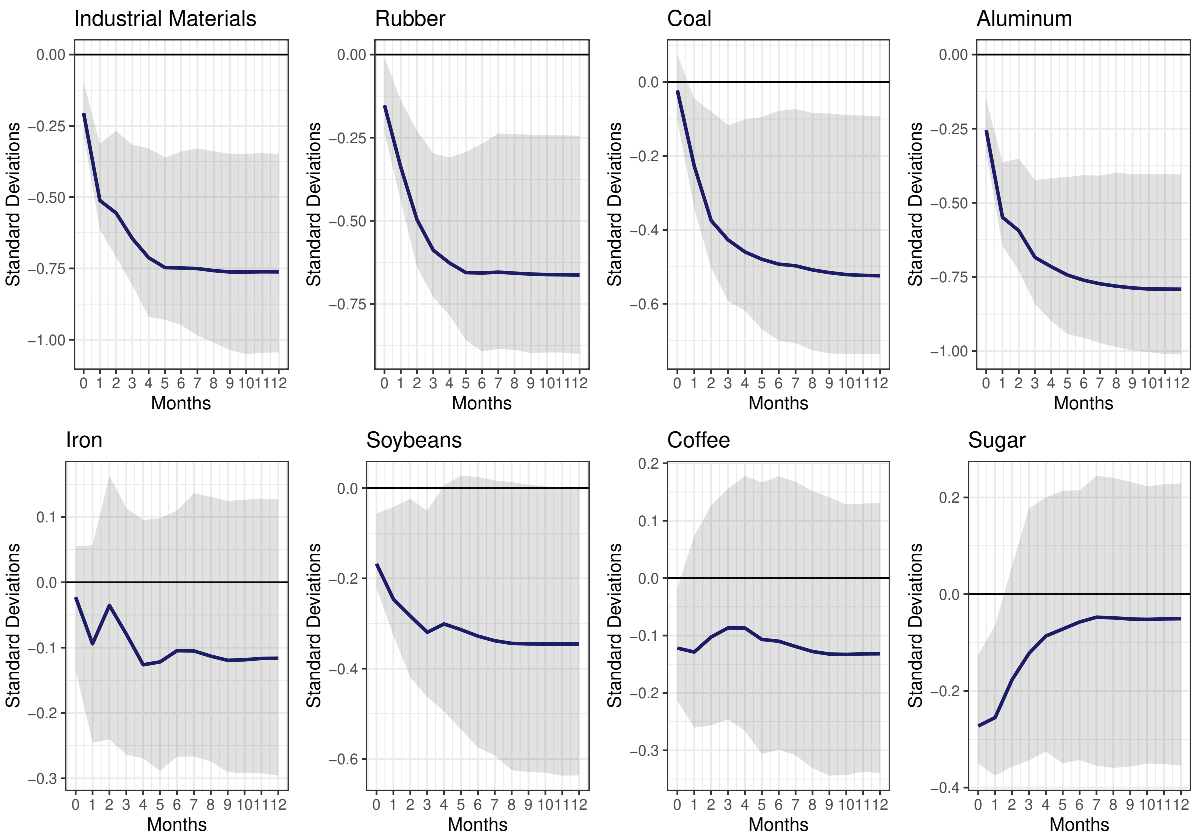
J. Westerlund and J.-P. Urbain. Cross-sectional averages versus principal components. *Journal of Econometrics*, 185(2):372–377, 2015.

Figure A.1: Response to a 1-Standard Deviation FTS Shock



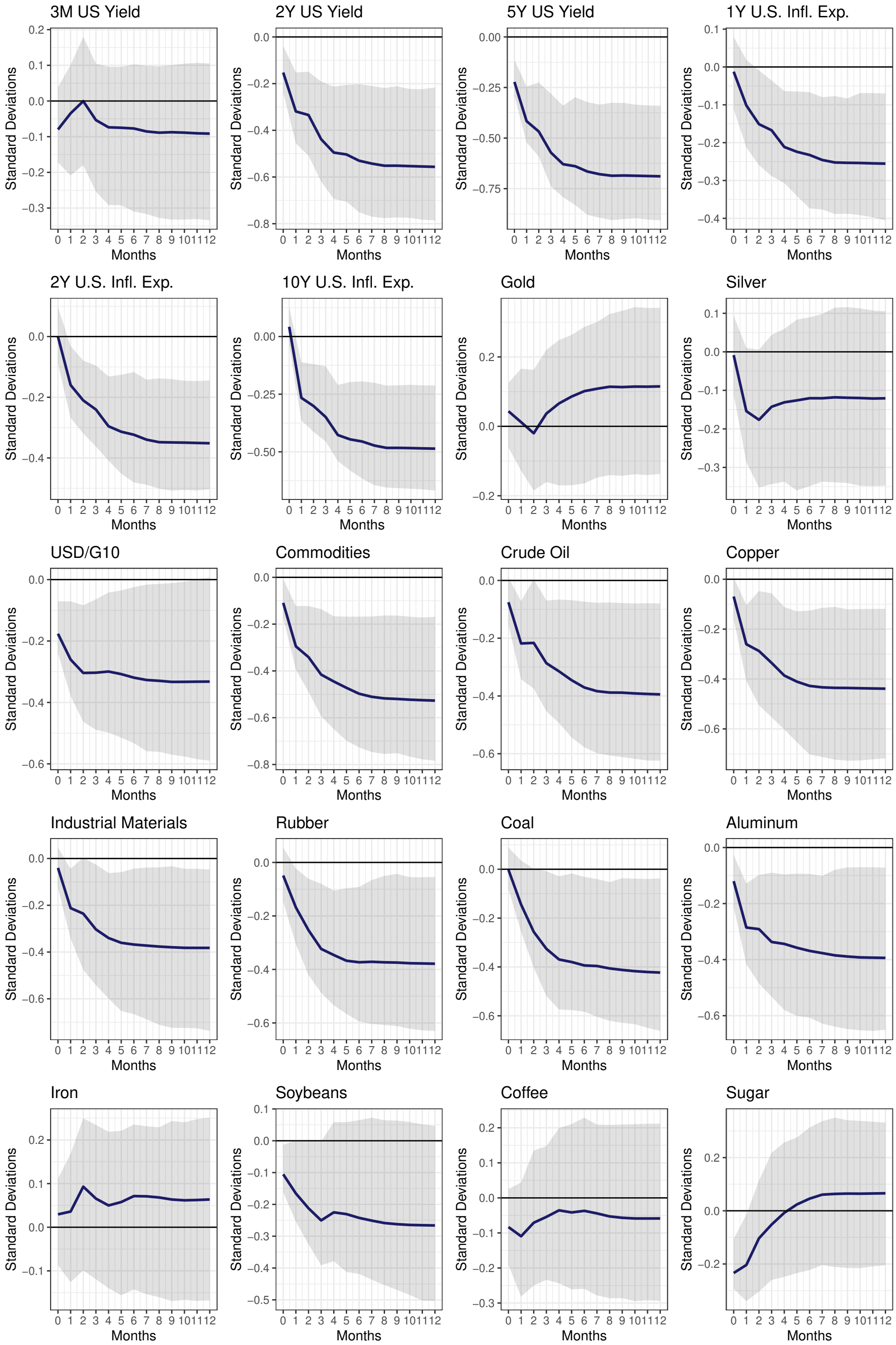
Cumulative response (in standard deviations) to a 1-standard deviation structural flight-to-safety (FTS) shock, FTS_t. 90% bootstrapped confidence bands.

Figure A.2: Response to a 1-Standard Deviation FTS Shock



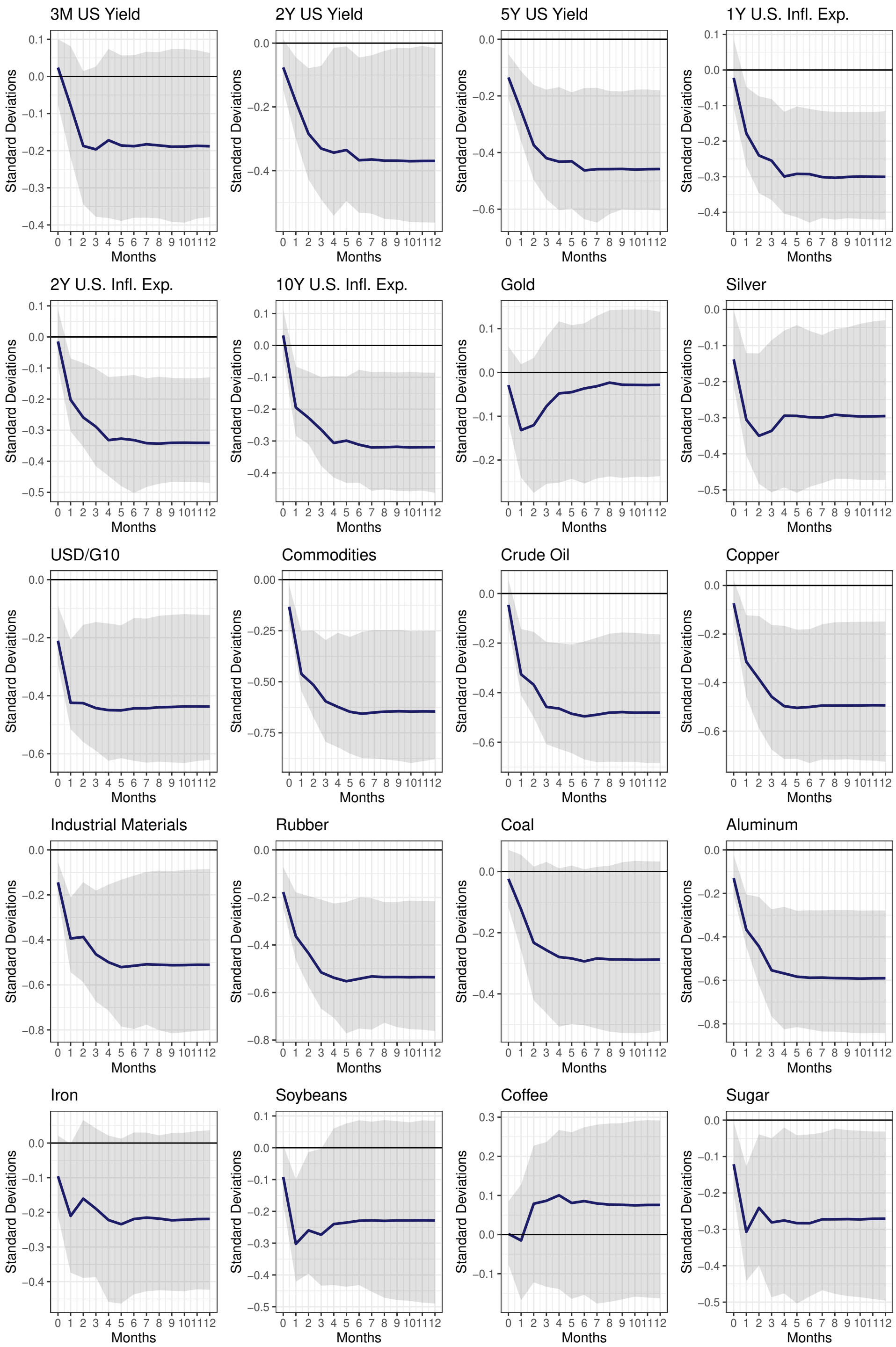
Cumulative response (in standard deviations) to a 1-standard deviation structural flight-to-safety (FTS) shock, FTS_t. 90% bootstrapped confidence bands.

Figure A.3: Response to a 1-Standard Deviation FTS Shock Orthogonal to Changes in log VIX



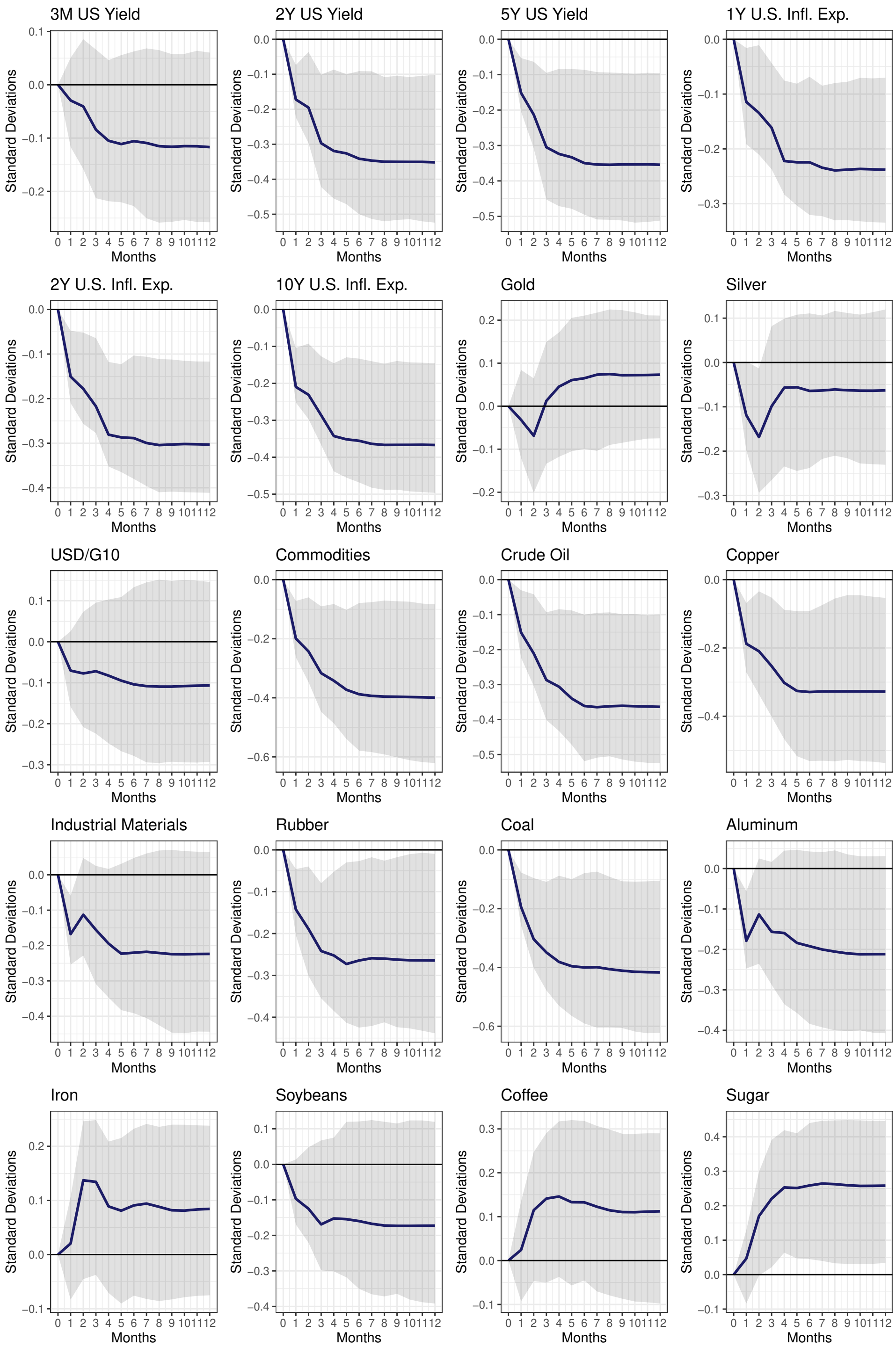
Cumulative response (in standard deviations) to a 1-standard deviation structural flight-to-safety (FTS) shock, FTS_t orthogonal to log VIX changes. In a first-stage, FTS_t is regressed on changes in the log VIX index. 90% bootstrapped confidence bands.

Figure A.4: Setting FTS Condition Threshold $c = 1$, Response to a 1-Standard Deviation FTS Shock



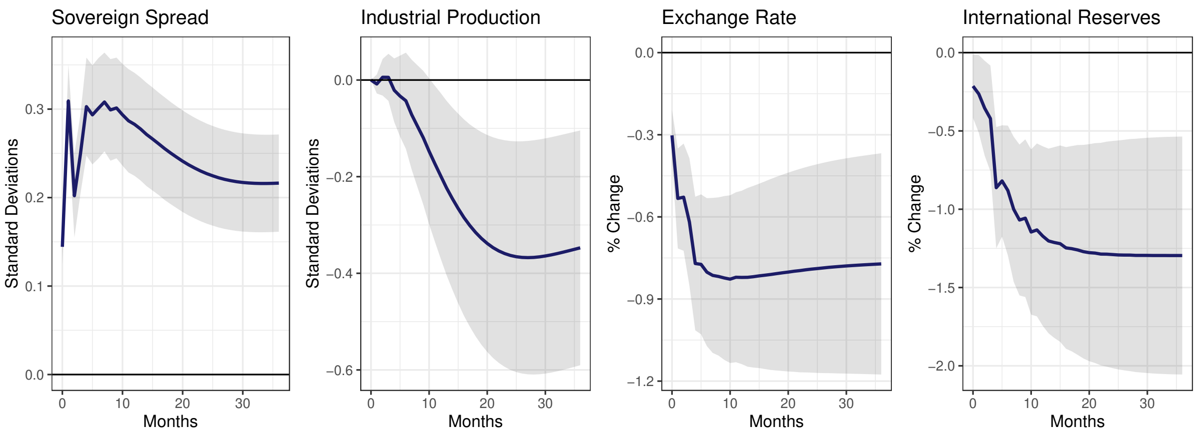
Cumulative response (in standard deviations) to a 1-standard deviation structural flight-to-safety (FTS) shock, FTS_t. 90% bootstrapped confidence bands.

Figure A.5: Response to a 1-Standard Deviation FTS Shock ordered Last in the Structural VAR



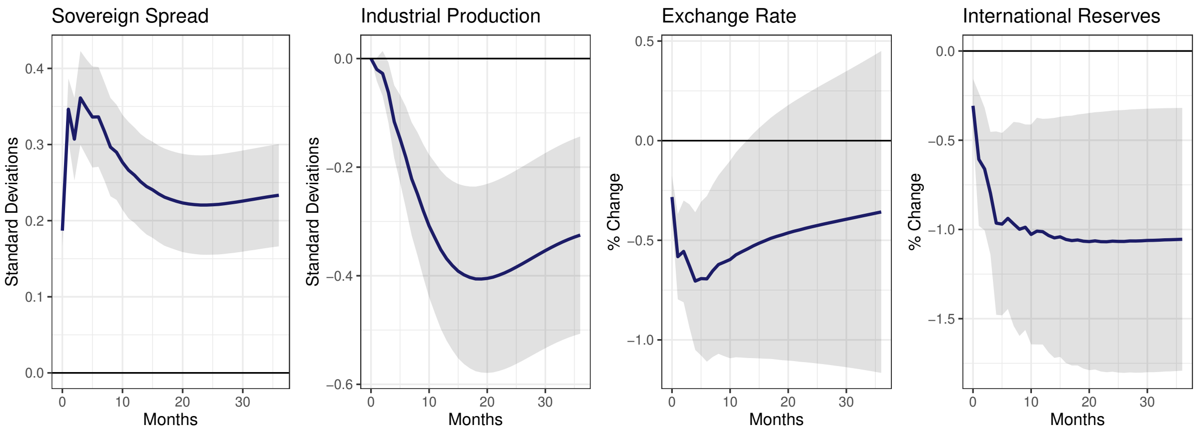
Cumulative response (in standard deviations) to a 1-standard deviation structural flight-to-safety (FTS) shock, FTS_t. 90% bootstrapped confidence bands.

Figure A.6: Response to a 1-Standard Deviation FTS Shock Orthogonal to Changes in log VIX



Cumulative MG Response (Equation 10) to a 1-standard deviation structural flight-to-safety shock, FTS_t. 95% non-parametric dispersion bands as computed in Equation 12. Log sovereign spread in monthly changes. Industrial production as year-over-year log change. Negative values imply exchange rate percent depreciation. International reserves in monthly log changes.

Figure A.7: Setting FTS Condition threshold $c = 1$, Response to a 1-Standard Deviation FTS Shock



Cumulative MG Response (Equation 10) to a 1-standard deviation structural flight-to-safety shock, FTS_t. 95% non-parametric dispersion bands as computed in Equation 12. Log sovereign spread in monthly changes. Industrial production as year-over-year log change. Negative values imply exchange rate percent depreciation. International reserves in monthly log changes.

Table A.1: Largest Daily Global FTS Shocks, 2000-2019

Description	Date	FTS_d
1. British referendum votes to exit E.U.	2016-06-24	4.89
2. Chinese Correction: Authorities announced plans to curb speculation	2007-02-27	4.74
3. U.S. President Trump controversy	2017-05-17	3.44
4. Lehman Brothers Bankruptcy	2008-09-15	3.33
5. Arab Spring - Instability in the Middle East and North Africa	2011-02-22	3.15
6. Italian political tensions, speculation of E.U. exit	2018-05-29	3.12
7. ECB announces no new emergency support for Greece; Greece calls for bailout referendum	2015-06-29	3.05
8. S&P downgraded Greece's credit rating to 'junk'	2010-04-27	3.04
9.GFC: Congress rejects bank bailout bill	2008-09-29	2.71
10. U.S. - China trade war intensifies	2019-08-05	2.61

February 24, 2020 would rank #4 and January 27, 2020 would rank #10 if the index was re-estimated through Feb 28, 2020 to account for the onset of the COVID-19 global pandemic.

Table A.2: Largest Daily Percent Wilshire 5000 Declines, 2000-2019

Description	Date	Change
1. GFC: NBER confirms U.S. recession	2008-12-01	-9.6%
2. 2008 GFC	2008-10-15	-9.4%
3. GFC: Congress rejects bank bailout bill	2008-09-29	-8.75%
4. 2008 GFC	2008-10-09	-7.8%
5. U.S. credit downgrade from AAA to AA+ by S&P	2011-08-08	-7.2%
6. 2008 GFC	2008-11-20	-7.1%
7. Tech Bubble Crash	2000-04-14	-6.6%
8. 2008 GFC	2008-11-19	-6.6%
9. 2008 GFC	2008-10-22	-6.1%
10. GFC: Fed communicates negative outlook	2008-10-07	-5.9%

Table A.3: Largest Daily Log VIX (Percent) Changes, 2000-2019

Description	Date	Change
1. "VIXplosion"	2018-02-05	+76.8%
2. Chinese Correction: Authorities announced plans to curb speculation	2007-02-27	+49.6%
3. U.S. credit downgrade from AAA to AA+ by S&P	2011-08-08	+40.5%
4. British referendum votes to exit E.U.	2016-06-24	+40.1%
5. China slowdown	2015-08-21	+38.1%
6. U.S. President Trump controversy	2017-05-17	+38.1%
7.China introduces new exchange rate mechanism ahead of potential Fed hike	2015-08-24	+37.3%
8. N. Korea announces plans to attack the U.S. Naval Base Guam	2017-08-10	+36.7%
9. U.S. China Trade war concerns	2018-10-10	+36.4%
10. Boston Marathon terrorist attack	2013-04-15	+35.9%

Table A.4: Domestic Financial Factors and the Impact of FTS shocks on Economic Activity

	Dependent variable:					
	18-Month Response of IP Growth					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.413*	0.702**	0.626**	0.752***	0.292	0.307
	(0.231)	(0.274)	(0.311)	(0.267)	(0.332)	(0.355)
6M Spread Response	−1.953***	−2.027***	−2.198***	−1.859***	−1.389**	−1.537**
	(0.444)	(0.462)	(0.591)	(0.506)	(0.575)	(0.671)
6M FX Response		23.964***	21.804**	17.548*	10.725	11.415
		(9.254)	(10.529)	(9.025)	(8.135)	(8.884)
6M Reserves Response			−12.022	−7.241	−25.492**	−25.577**
			(9.114)	(7.938)	(11.234)	(11.796)
$\ln(ETF_i + 1)$				−0.109***	−0.082**	−0.080**
				(0.039)	(0.040)	(0.040)
Commodity Exporter						0.143
						(0.210)
6M FX × 6M Reserves Response					−1,263.024**	−1,295.828**
					(514.562)	(513.679)
Observations	34	34	34	34	34	34
R^2	0.270	0.370	0.432	0.538	0.593	0.601
Adjusted R^2	0.247	0.329	0.375	0.474	0.520	0.513

Robust standard errors. *, **, *** correspond to significance at the 10, 5, and 1 percent level, respectively. Dependent variable is the cumulative 18-month expected response of IP growth (in SDs) to a 1-SD FTS shock (Dependent and independent variable descriptions found in Equation 13). The last independent variable is the interaction of the 6-month cumulative response of country i's exchange rate to a 1-SD FTS shock and the 6-month cumulative response of country i's international reserves. IP growth and changes in log spreads are in units of standard deviations. Exchange rate and reserves are in log changes. Commodity Exporter refers to an indicator variable denoting whether the country is a commodity exporter defined as having greater than 35% of total exports as commodities and greater than 5% of total trade (Aslam et al. [2016]).

Table A.5: Domestic Financial Factors and the Impact of VIX shocks on Economic Activity

	Dependent variable:					
	18-Month Response of IP Growth					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	−0.094	−0.095	−0.010	0.277	0.020	0.025
	(0.322)	(0.332)	(0.312)	(0.307)	(0.296)	(0.291)
6M Spread Response	−0.789	−0.764	−1.107*	−0.956	−0.629	−0.719
	(0.548)	(0.685)	(0.637)	(0.582)	(0.597)	(0.648)
6M FX Response		1.552	−0.373	−4.041	−10.140	−10.737
		(18.582)	(19.203)	(13.690)	(8.099)	(8.725)
6M Reserves Response			−10.773	−4.113	−9.865	−10.360
			(7.616)	(8.206)	(7.853)	(8.549)
$\ln(ETF_i + 1)$				−0.131***	−0.100***	−0.099***
				(0.049)	(0.038)	(0.038)
Commodity Exporter						0.093
						(0.180)
6M FX × 6M Reserves Response					−1,614.727**	−1,655.827**
					(646.421)	(645.686)
Observations	34	34	34	34	34	34
R^2	0.061	0.062	0.139	0.360	0.508	0.513
Adjusted R^2	0.032	0.002	0.053	0.272	0.420	0.405

Robust standard errors. *, **, *** correspond to significance at the 10, 5, and 1 percent level, respectively. Dependent variable is the cumulative 18-month expected response of IP growth (in SDs) to a 1-SD log VIX shock replacing the FTS shock in Equation 9 (Dependent and independent variable descriptions found in Equation 13). The last independent variable is the interaction of the 6-month cumulative response of country i's exchange rate to a 1-SD FTS shock and the 6-month cumulative response of country i's international reserves. IP growth and changes in log spreads are in units of standard deviations. Exchange rate and reserves are in log changes. Commodity Exporter refers to an indicator variable denoting whether the country is a commodity exporter defined as having greater than 35% of total exports as commodities and greater than 5% of total trade (Aslam et al. [2016]).

Table A.6: Domestic Financial Factors and the Impact of Global Financial Cycle shocks on Economic Activity

	Dependent variable:					
	18-Month Response of IP Growth					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	−0.315	−0.190	−0.198	0.120	−0.196	−0.198
	(0.289)	(0.281)	(0.277)	(0.287)	(0.291)	(0.298)
6M Spread Response	−0.734	−0.628	−0.920*	−0.842*	−0.798*	−0.741
	(0.457)	(0.518)	(0.482)	(0.441)	(0.440)	(0.544)
6M FX Response		12.816	11.913	8.052	−6.002	−5.674
		(12.751)	(13.507)	(11.011)	(10.860)	(11.204)
6M Reserves Response			−9.935	−4.141	−19.640*	−19.138
			(8.744)	(9.175)	(11.730)	(11.789)
$\ln(ETF_i + 1)$				−0.121**	−0.079*	−0.080*
				(0.055)	(0.040)	(0.043)
Commodity Exporter						−0.054
						(0.232)
6M FX × 6M Reserves Response					−1,155.667**	−1,137.756**
					(512.268)	(520.142)
Observations	34	34	34	34	34	34
R^2	0.067	0.125	0.181	0.328	0.436	0.438
Adjusted R^2	0.038	0.069	0.099	0.235	0.336	0.313

Robust standard errors. *, **, *** correspond to significance at the 10, 5, and 1 percent level, respectively. Dependent variable is the cumulative 18-month expected response of IP growth (in SDs) to a 1-SD log Global Financial Cycle shock of Miranda-Agrippino and Rey [2020] replacing the FTS shock in Equation 9 (Dependent and independent variable descriptions found in Equation 13). The last independent variable is the interaction of the 6-month cumulative response of country i's exchange rate to a 1-SD FTS shock and the 6-month cumulative response of country i's international reserves. IP growth and changes in log spreads are in units of standard deviations. Exchange rate and reserves are in log changes. Commodity Exporter refers to an indicator variable denoting whether the country is a commodity exporter defined as having greater than 35% of total exports as commodities and greater than 5% of total trade (Aslam et al. [2016]).

Online Supplement to

"Global Flights-to-Safety and Macroeconomic Adjustment in Emerging Markets"

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University of Southern California, USA

This Online Supplement is organized in four sections. Section S1 provides detail on relevant data and sources. Section S2 provides additional results and further robustness checks. Section S3 describes a method to separate excess risk sentiment from the global demand component embedded in Flight-to-Safety shocks, providing additional results on the effects of flight-to-safety shocks.

S1 Data

Data is collected from a variety of sources. To construct global flight-to-safety shocks, the underlying daily data on the VIX Index, Wilshire 5000 index, 10-year Treasury yields, U.S. corporate high yield spreads, and exchange rates are taken from the FRED database. The daily data is collected spans January 2000 to August 2019. The daily data is eventually aggregated to a monthly frequency for further analysis.

Monthly average sovereign spreads are measured with J.P. Morgan EMBI indices. The sample contains monthly data on spreads for 34 countries over the period January 2000 to August 2019. All countries have at least 99 observations, Log changes in EMBI spreads are computed as:

$$\Delta s_{it} = \ln(\frac{S_{it}}{S_{i,t-1}}),$$

where S_{it} is the average EMBI spread level for country i over month t. Because the analysis relies on changes in the log EMBI spread, the bulk of summary statistics are reported on Δs_{it}. Table S.1 reports summary statistics on changes in sovereign spreads across countries. outlier observations of logged EMBI changes greater than +200% or less than -100% are removed.

Monthly industrial production data across countries is taken from the World Bank. Year-on-Year changes in log industrial production are computed as:

$$\Delta y_{it} = \ln(\frac{Y_{it}}{Y_{i,t-12}}),$$

where Y_{it} is the nominal industrial production of country i in month t. Summary statistics for year-over-year changes in log industrial production are reported in Table S.2. Iraq experienced very large swings in industrial production during the early 2000's when it was invaded and under military occupation. This is visible in her summary statistics.

Table S.3 report summary statistics on select commodity and financial market variables at the monthly frequency. The values are monthly average changes, not end-of-month changes.

For emerging markets, country-specific measures of nominal USD exchange rates are from the IMF. These are monthly averages, with changes in log exchange rates interpreted as log returns. Positive changes in denote domestic appreciation vis-a-vis the USD. Country-specific measures of international reserves are taken from the IMF as well. These are denominated in USD. Reserves growth rates are computed as changes in log monthly reserves, where positive monthly growth denotes reserves accumulation.

Data on daily equity index prices across 32 countries are taken from Bloomberg to construct the global average realized volatility measure, $GVOL_t$, similar to that of Cesa-Bianchi et al. [2020]. Data on monthly estimates of the global financial cycle from Miranda-Agrippino and Rey [2020], $GFCY_t$, are available through the authors' website.

Table S.1: Summary Statistics for Changes in Log EMBI Spread

Country	T	Min	Max	Mean	Median	SD	Median Level
Argentina	235	-0.730	0.686	0.009	-0.004	0.139	722.793
Belarus	107	-0.248	0.511	-0.007	-0.014	0.116	625.614
Brazil	235	-0.204	0.525	-0.005	-0.019	0.103	270.003
Chile	235	-0.368	0.487	-0.000	-0.002	0.096	139.650
China	235	-0.808	0.659	0.002	0.000	0.127	138.411
Colombia	235	-0.255	0.670	-0.004	-0.020	0.112	216.005
Cote d'Ivoire	235	-0.453	0.305	-0.003	-0.005	0.075	1106.238
Croatia	235	-0.270	0.371	-0.045	-0.070	0.103	257.671
Ecuador	235	-0.769	0.806	-0.007	-0.016	0.139	788.271
Egypt	217	-0.561	0.986	0.010	-0.010	0.187	349.198
El Salvador	208	-0.216	0.550	0.003	-0.006	0.093	376.053
Gabon	140	-0.267	0.646	0.003	-0.006	0.126	425.400
Hungary	235	-0.709	0.823	0.001	-0.002	0.167	123.800
Indonesia	182	-0.300	0.733	-0.004	-0.017	0.113	239.111
Iraq	160	-0.231	0.346	0.000	-0.003	0.095	520.688
Jordan	103	-0.348	0.374	-0.000	0.010	0.081	382.145
Kazakhstan	146	-0.279	0.669	0.001	-0.010	0.133	298.227
Lithuania	117	-0.459	0.395	-0.020	-0.023	0.151	123.726
Malaysia	235	-0.284	0.589	-0.001	-0.007	0.104	141.806
Mexico	235	-0.221	0.584	-0.001	-0.010	0.092	219.976
Pakistan	218	-0.525	0.523	-0.041	-0.024	0.179	512.429
Peru	235	-0.248	0.663	-0.005	-0.019	0.115	194.396
Philippines	235	-0.226	0.561	-0.006	-0.007	0.101	217.405
Poland	235	-0.671	0.582	-0.007	0.008	0.138	109.399
Russia	235	-0.266	0.629	-0.010	-0.025	0.117	241.053
Senegal	99	-0.166	0.213	-0.001	-0.003	0.077	450.697
South Africa	235	-0.261	0.650	0.001	-0.004	0.110	236.514
Sri Lanka	141	-0.285	0.658	-0.001	-0.009	0.115	412.982
Tunisia	207	-0.525	0.481	-0.018	-0.049	0.123	209.755
Turkey	235	-0.241	0.532	0.001	-0.008	0.108	305.410
Ukraine	231	-0.475	0.974	-0.006	-0.012	0.148	620.636
Uruguay	218	-0.340	0.576	-0.002	-0.019	0.114	230.800
Venezuela	235	-0.209	0.605	0.011	0.001	0.109	1038.486
Vietnam	164	-0.283	0.665	-0.002	-0.005	0.137	249.750

Summary statistics for Δs_{it} (Equation 9), monthly changes in the log EMBI spread. Column 8, Median Level, reports the median level of each country's EMBI spread. SD refers to standard deviation.

Table S.2: Summary Statistics for Year-over-Year Change in Log Industrial Production

Country	T	Min	Max	Mean	Medan	SD
Argentina	235	-0.222	0.245	0.022	0.023	0.078
Belarus	151	-0.109	1.997	0.259	0.136	0.436
Brazil	235	-0.170	0.190	0.012	0.013	0.064
Chile	235	-0.131	0.140	0.021	0.027	0.044
China	235	0.038	0.207	0.116	0.114	0.044
Colombia	235	-0.143	0.163	0.025	0.020	0.054
Cote d'Ivoire	195	-0.501	0.581	0.027	0.035	0.163
Croatia	235	-0.142	0.131	0.014	0.017	0.052
Ecuador	235	-0.170	0.491	0.043	0.050	0.078
Egypt	175	-0.145	0.410	0.044	0.034	0.081
El Salvador	235	-0.046	0.079	0.014	0.014	0.023
Gabon	235	-0.377	0.426	-0.005	0.018	0.137
Hungary	235	-0.302	0.291	0.046	0.056	0.087
Indonesia	235	-0.136	0.345	0.040	0.038	0.053
Iraq	235	-0.830	11.500	0.144	0.087	0.860
Jordan	235	-0.229	0.286	0.022	0.015	0.078
Kazakhstan	235	-0.096	0.414	0.072	0.059	0.083
Lithuania	235	-0.260	0.381	0.048	0.050	0.088
Malaysia	235	-0.176	0.234	0.042	0.040	0.063
Mexico	235	-0.177	0.148	0.016	0.022	0.048
Pakistan	235	-0.195	0.319	0.049	0.039	0.084
Peru	235	-0.141	0.222	0.037	0.037	0.073
Philippines	235	-0.287	0.360	0.025	0.025	0.110
Poland	235	-0.153	0.234	0.054	0.055	0.059
Russian	235	-0.170	0.263	0.037	0.040	0.054
Senegal	151	-0.224	0.609	0.060	0.042	0.127
South Africa	235	-0.232	0.100	0.012	0.018	0.051
Sri Lanka	104	-0.143	0.193	0.025	0.020	0.059
Tunisia	235	-0.177	0.165	0.007	0.000	0.050
Turkey	235	-0.240	0.294	0.055	0.065	0.092
Ukraine	200	-0.308	0.221	0.011	0.023	0.107
Uruguay	200	-0.311	0.572	0.048	0.037	0.127
Venezuela	235	-0.648	1.832	-0.045	-0.015	0.229
Vietnam	128	-0.504	0.679	0.104	0.103	0.214

Summary statistics for Δy_{it} (Equation 9). Iraq's large minimum and maximum driven by the war period in the early 2000s. SD refers to standard deviation.

Table S.3: Summary Statistics for Select Financial and Commodity Market Variables

Market Variable (Monthly)	T	Mean	SD	Min	Pctl(25)	Pctl(75)	Max
VIX	235	−0.001	0.167	−0.373	−0.098	0.068	0.708
U.S. High Yield Credit Spread	235	−0.0005	0.088	−0.223	−0.059	0.043	0.486
Wilshire 5000 Index	235	0.0002	0.002	−0.008	−0.001	0.002	0.005
3-month Treasury Yield	235	−0.004	0.329	−1.738	−0.072	0.065	2.025
2-year Treasury Yield	235	−0.006	0.124	−0.568	−0.070	0.061	0.316
5-year Treasury Yield	235	−0.006	0.100	−0.411	−0.058	0.046	0.360
10-year Treasury Yield	235	−0.006	0.070	−0.378	−0.046	0.034	0.194
1-year Inflation Expectations	235	−0.0001	0.004	−0.013	−0.002	0.002	0.017
2-year Inflation Expectations	235	−0.0001	0.002	−0.006	−0.001	0.001	0.008
10-year Inflation Expectations	235	−0.007	0.101	−0.368	−0.067	0.059	0.253
USD/G10 Exchange Rate	235	−0.0002	0.019	−0.050	−0.013	0.013	0.082
Copper Price	235	0.005	0.065	−0.354	−0.025	0.038	0.230
WTI Crude Oil Price	235	0.003	0.087	−0.332	−0.045	0.060	0.214
Gold Price	235	0.007	0.037	−0.124	−0.016	0.032	0.115

Inflation expectations are monthly changes (not logged). All others are monthly changes in logs. Inflation expectations are estimated using the method of Haubrich et al. [2012].

Table S.4: U.S. Traded ETFs Granting Exposure to an EM Country

	Country	Number of ETFs
1	Argentina	112
2	Belarus	0
3	Brazil	281
4	Chile	118
5	China	571
6	Colombia	101
7	Cote d'Ivoire	0
8	Croatia	1
9	Ecuador	0
10	Egypt	60
11	El Salvador	0
12	Gabon	0
13	Hungary	58
14	Indonesia	127
15	Iraq	3
16	Jordan	3
17	Kazakhstan	6
18	Lithuania	0
19	Malaysia	193
20	Mexico	340
21	Pakistan	47
22	Peru	6
23	Philippines	109
24	Poland	106
25	Russia	162
26	Senegal	0
27	South Africa	231
28	Sri Lanka	2
29	Tunisia	0
30	Turkey	107
31	Ukraine	7
32	Uruguay	0
33	Venezuela	0
34	Vietnam	1

Source: etfdb.com. Data collected as of October 2020.

S2 Additional Results and Robustness

S2.1 Emerging markets: local projection impulse responses

To check whether the results for the panel of emerging markets are robust to model specification, I estimate impulse response functions using Local Projections (Jordà [2005]) rather than the structural VAR approach. I estimate the following local projection regressions for the financial variables, sovereign spreads, exchange rate returns, and log changes in international reserves:

$$
\begin{aligned}
[\Delta s_{i,t+h}, \Delta FX_{i,t+h}, \Delta res_{i,t+h}] = \alpha_i(h) + \sum_{p=0}^{1} \beta_{i1p}(h)\Delta\mathcal{Y}_{US,t-p} + \sum_{p=0}^{1} \beta_{i2p}(h)\Delta\mathcal{Y}_{i',t-p} \\
+ \sum_{p=0}^{1} \beta_{i3p}(h)\Delta y_{i,t-p} + \sum_{p=0}^{1} \beta_{i4p}(h)FTS_{t-p} + \sum_{p=1}^{2} \beta_{i5p}(h)\Delta\mathcal{S}_{i',t-p} + \sum_{p=1}^{2} \beta_{i6p}(h)\Delta s_{i,t-p} \\
+ \sum_{p=1}^{2} \beta_{i7p}(h)\Delta FX_{i,t-p} + \sum_{p=1}^{2} \beta_{i8p}(h)\Delta res_{i,t-p} + e_{i,t+h}. \quad \text{(S.1)}
\end{aligned}
$$

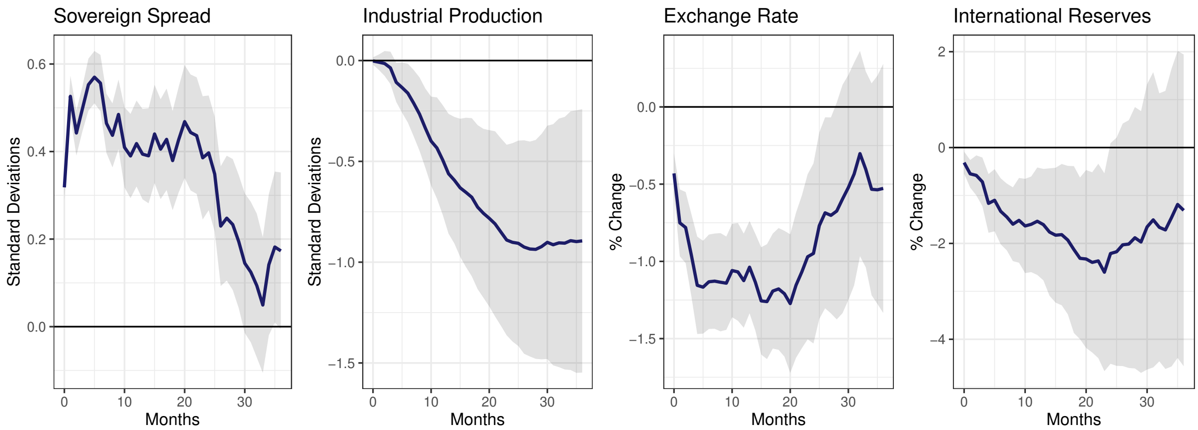
To maintain the same recursive identification structure as in the multi-country SVAR, notice that for financial variables (spreads, exchange rates and reserves), FTS_t has a contemporaneous effect on financial variables as do the measures of economic activity, given in Equation S.1. Meanwhile for the local projections corresponding to industrial production, $\Delta y_{i,t+h}$ is given by:

$$
\begin{aligned}
\Delta y_{i,t+h} = \alpha_i(h) + \sum_{p=0}^{1} \beta_{i1p}(h)\Delta\mathcal{Y}_{US,t-p} + \sum_{p=0}^{1} \beta_{i2p}(h)\Delta\mathcal{Y}_{i',t-p} + \sum_{p=1}^{2} \beta_{i3p}(h)\Delta y_{i,t-p} \\
+ \sum_{p=0}^{1} \beta_{i4p}(h)FTS_{t-p} + \sum_{p=1}^{2} \beta_{i5p}(h)\Delta\mathcal{S}_{i',t-p} + \sum_{p=1}^{2} \beta_{i6p}(h)\Delta s_{i,t-p} \\
+ \sum_{p=1}^{2} \beta_{i7p}(h)\Delta FX_{i,t-p} + \sum_{p=1}^{2} \beta_{i8p}(h)\Delta res_{i,t-p} + e_{i,t+h}. \quad \text{(S.2)}
\end{aligned}
$$

In Equation S.2, U.S. economic activity, $\Delta\mathcal{Y}_{US,t}$ and the EM growth factor $\Delta\mathcal{Y}_{i',t}$ enter contemporaneously on the right-hand-side. FTS shocks also enter contemporaneously while the other financial variables enter with a lag. This way, the impact of the FTS shock will include both it's direct effect on $\Delta y_{i,t+h}$ but also the effect through financial variables.

The local projections from a global FTS shock on sovereign spreads, industrial production, exchange rates and international reserves are then plotted as the Mean Group estimate of β_{i40} estimates, respectively in Figure S.1. Notice that the responses are con-

Figure S.1: Emerging Markets: Average Response to a 1-Standard Deviation FTS Shock Using Local Projections



Cumulative MG Response from local projection estimates (Equations S.1 and S.2) to a 1-standard deviation structural flight-to-safety shock, FTS_t. 95% non-parametric dispersion bands as computed in Equation 12. Log sovereign spread in monthly changes. Industrial production as year-over-year log change. Negative values imply exchange rate percent depreciation. International reserves in monthly log changes.

sistent in direction and closely approximate in size compared to the baseline MG impulse responses estimated form the mutli-country SVAR (Equation 9).

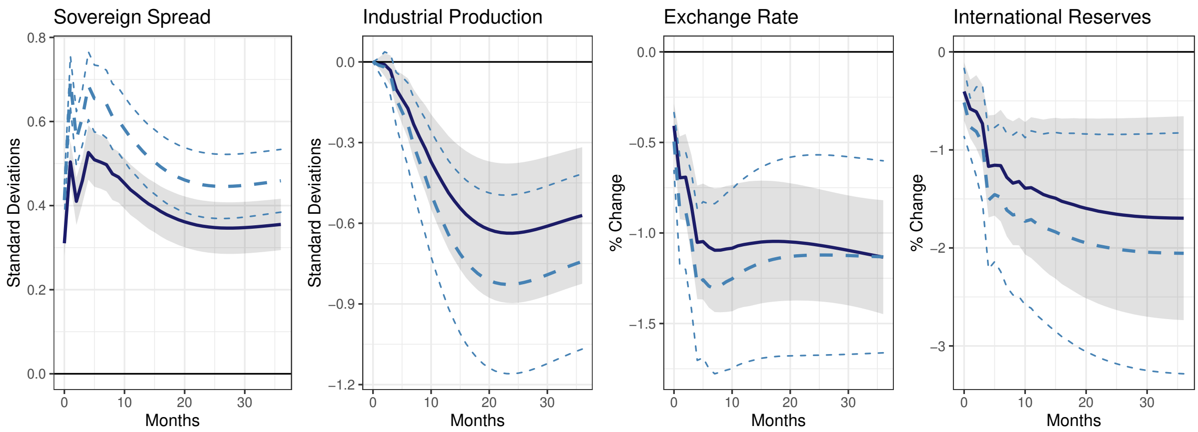
S2.2 Asymmetries: Positive versus negative FTS shocks

The prevailing VAR model assumes FTS shocks are symmetric – negative (risk-on) and positive (risk-off) movements are treated equally. However, there is good reason to believe that flight-to-safety as risk-off shocks have an asymmetric impact, likely much more severe than the inverse risk-on (or negative change in the FTS index). Introducing non-linearities into a VAR system comes with its own challenges. and does not guarantee parameter stability. A simple yet robust approach to compare the linear IRFs to the IRF when we allow asymmetry is to estimate the MG IRF for the *marginal* added impact of an FTS shock after allowing for asymmetries, and add that to the standard MG IRF under the linear case. Specifically, the asymmetry imposed is that positive FTS shocks (risk-off) can impact the system differently from negative FTS shocks (risk-on).

Implementing this econometric design takes two steps. First, I include in the linear VAR contemporaneous FTS shocks, FTS_t. Then, I add an additional equation to the VAR to capture the asymmetry, $FTS_t \times \mathbf{1}_{FTS_t>0}$. This series reflects FTS shocks which are strictly positive, setting negative (risk-on) shocks to zero. Because the VAR controls for contemporanous FTS_t fully, shocking the $FTS_t \times \mathbf{1}_{FTS_t>0}$ generates the IRF for the marginal asymmetric effect of a positive FTS shock above and beyond the linear effect.

Figure S.2 shows the MG IRF from the standard, linear IRF and compares it to

Figure S.2: Emerging Markets: Response to a 1-Standard Deviation Positive Symmetric FTS Shock (Solid) and After Allowing for Asymmetry (Dashed)



Cumulative MG Response (Equation 10) to a 1-standard deviation structural flight-to-safety shock, FTS_t which is symmetric (solid) and after allowing positive (risk-off) shocks to have an asymmetric impact compared to negative (risk-on) FTS shocks (dashed). 95% non-parametric dispersion bands as computed in Equation 12. Log sovereign spread in monthly changes. Industrial production as year-over-year log change. Negative values imply exchange rate percent depreciation. International reserves in monthly log changes.

the IRF from a FTS shock once asymmetry is allowed for. When the model allows differential effects of positive and negative FTS shocks, the impact of a positive FTS shock strengthens across all four variables of interest. This highlights that treating positive and negative FTS shocks symmetrically tends to downward-bias the impact of positive FTS shocks (risk-off) and induces upward-bias in the impact of negative FTS shocks (risk-on). Indeed, risk-off or positive FTS shocks have a substantially larger absolute impact on emerging market dynamics than negative FTS shocks, or risk-on.

S2.3 A model-free measure of global flights-to-safety

The global FTS index, FTS_t relies on an estimate of conditional volatility. Therefore, it needs to use the full sample for estimation, which may induce look-ahead biases, and comes with parametric assumptions. This poses an issue if one's primary objective is to forecast. On the other hand, this is less of an issue if one's goal is to combine ex ante and ex post information for explanatory purposes. The latter is the main objective of this paper, and similar full-sample approaches are taken in estimating global financial shocks from realized volatility in Cesa-Bianchi et al. [2020] and in constructing the Global Financial Cycle in Miranda-Agrippino and Rey [2020].[S1]

[S1] In Cesa-Bianchi et al. [2020] to identify financial shocks, the authors regress global realized volatility ($GVOL_t$) on global real GDP growth over the full sample period. In Miranda-Agrippino and Rey [2020], the factor model employed to recover the common factor in risky asset prices takes information from the full sample.

As an alternative, I present a model-free measure of monthly global FTS shocks using daily changes in the log VIX index. Denote this measure the global FTS-VIX shock series, or $FTS_t(v)$, which is defined as:

$$FTS_t(v) = \sum \ln VIX_d(t) - \sum \ln VIX_d(t)|d \notin FTS = \sum \ln VIX_d(t)\mathbf{1}_d, \qquad \text{(S.3)}$$

Where the month t total change in the log VIX index is the sum of two components, $FTS_t(v)$ and $\sum \ln VIX_d(t)|d \notin FTS$. The first term is the sum of log VIX changes in month t which occurs amid flight-to-safety, or risk-on/risk-off days. The second term is the sum of log VIX changes in the same month which occured on all remaining days. The indicator 1_d, as previously, imposes the flight-to-safety condition, thereby identifying risk-off and risk-on days using the daily returns across the candidate assets, denoted r_{ad}:

$$\mathbf{1}_d \begin{cases} 1 & \text{if } \{r_{1d}, r_{5d}\} > c \cap \{r_{2d}, r_{3d}, r_{4d}, r_{6d}\} < -c \quad \text{‘\textit{Risk-Off}’} \\ 1 & \text{if } \{r_{1d}, r_{5d}\} < -c \cap \{r_{2d}, r_{3d}, r_{4d}, r_{6d}\} > c \quad \text{‘\textit{Risk-On}’} \\ 0 & \text{otherwise.} \end{cases} \qquad \text{(S.4)}$$

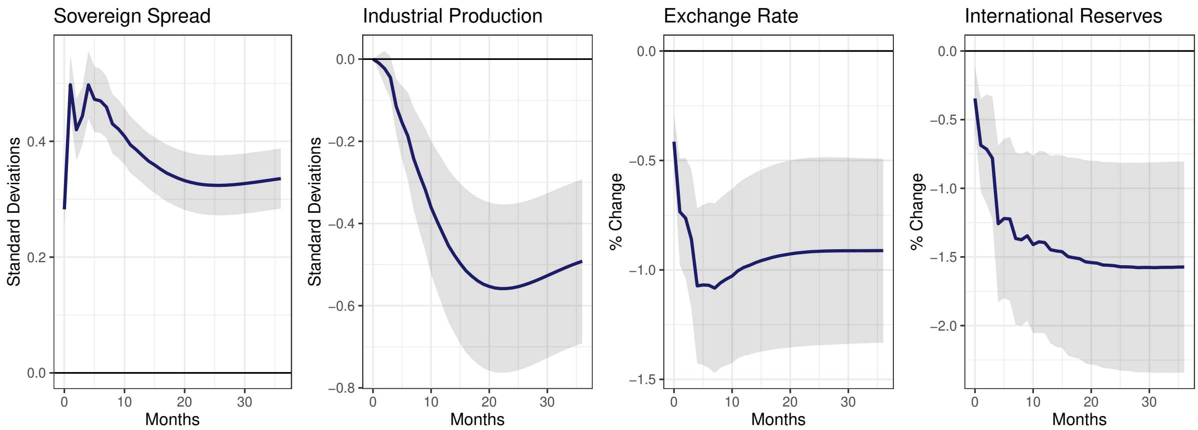
This way I first classify each daily change in the VIX as belonging to a risk-on/risk-off event, or not. Then within each of these groups, summing the daily changes to the monthly level I break the total change in the log VIX index over month t into the component that occurred amid risk-on/risk-off, and the remainder. The former is a model-free measure of global FTS, denoted $FTS_t(v)$ which uses changes in the VIX index amid flights-to-safety (or risk-on/risk-off). To validate the new measure as a proxy for the baseline measure, the estimated correlation between FTS_t and $FTS_t(v)$ is 0.87; the model-free measure is highly correlated with the the baseline FTS index.

Baseline MG IRFs are reported in Figure S.3 using the model-free FTS shock series, $FTS_t(v)$, and the results are largely unchanged compared to the baseline impulse response functions shown in Figure 8.

S3 Flight-to-Safety, Excess Risk Sentiment, and Global Demand

Large global shocks measured with asset prices reflect both risk sentiment and physical risk (global demand) - the latter referring to changing beliefs over future fundamentals. It's evident that global FTS shocks, a product of asset price movements, exhibits clear links to global demand shown by their impact on commodity prices and U.S. inflation expectations and also by the economic relevance of the events triggering them. While the impact of FTS shocks itself is the main focus of this paper, here I separate the effects

Figure S.3: Average Response to a 1-Standard Deviation FTS Shock Using the Model Free Measure, $FTS_t(v)$



Cumulative MG Response (Equation 10) to a 1-standard deviation structural flight-to-safety shock, $FTS_t(v)$ defined in Equation S.3 as the model-free version of the shock series. 95% non-parametric dispersion bands as computed in Equation 12. Log sovereign spread in monthly changes. Industrial production as year-over-year log change. Negative values imply exchange rate percent depreciation. International reserves in monthly log changes.

induced by an excess risk sentiment component and a global demand component of FTS shocks to better understand the two forces.

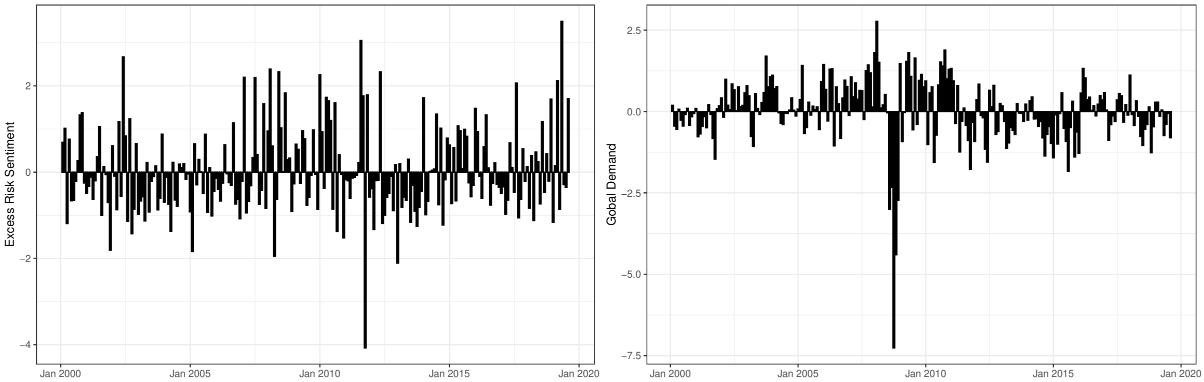
I propose a simple reduced-form separation of FTS shocks into their global demand and excess risk sentiment components. This is accomplished by estimating a principal components regression (PCR) of global FTS shocks on the common factor in world commodity prices, an established proxy for global demand. The obtained residual then reflects the component of global FTS that is left unexplained by the contemporaneous adjustment in commodity prices, which I refer to as excess risk sentiment. More explicitly, I define excess risk sentiment as the component of risk affecting financial asset prices as pure risk premia; it is *excess* in that it has no causal effect on fundamental global demand and simply serves to compensate risk aversion.

Suppose FTS shocks were made up of two orthogonal components,

$$FTS_t = G_t + V_t, \tag{S.5}$$

where G_t reflects global demand, and V_t is the excess risk sentiment. It's 'excess' because it is the risk sentiment reflected in asset prices above and beyond whatever effect risk has had on global demand (which is absorbed in G_t). However these two components are unobserved, and therefore must be estimated. Therefore to recover the excess risk sentiment component, I regress FTS_t on an estimate for global demand $\widehat{G}_t$, which I measure as the common factor in commodity prices:

Figure S.4: Separating Global Flights-to-Safety Shocks into Excess Risk Sentiment ($\widehat{V}_t$) and Global Demand ($\widehat{G}_t$)



Both series are normalized to have unit standard deviation.

$$FTS_t = \underbrace{\hat{\beta}\boldsymbol{\gamma}\Delta\mathbf{C}_t}_{\widehat{G}_t} + \epsilon_t^V, \quad \widehat{V}_t = \epsilon_t^V, \tag{S.6}$$

where

$$\boldsymbol{\gamma}\Delta\mathbf{C}_t = \sum_{k=1}^{K} \gamma_k \Delta c_{k,t}. \tag{S.7}$$

$\Delta\mathbf{C}_t$ is a $T \times k$ matrix of log returns from a broad set of k commodity prices, and coefficients γ_k as set such $\boldsymbol{\gamma}'\Delta\mathbf{C}_t$ reflects the first principal component of the space of commodity returns (i.e. the vector which maximizes the variance across the space of commodities). Specifically, I estimate $\widehat{G}_t$ using Principal Components Analysis (PCA) over a broad set of 66 commodity prices. The first principal component is our estimate of $\widehat{G}_t$. Each commodity price series is log-differenced and standardized. Then, by then regressing FTS_t on the common commodity factor, I define the obtained residual ϵ_t^V as excess risk sentiment $\widehat{V}_t$.

Figure S.4 shows the decomposition of FTS shocks into risk premia and global demand, respectively. Starkly, the 2008-2009 global financial crisis is identified as a large, negative global demand shock. August, September, and October 2008 reflect deep negative global demand pressure, each exceeding -3 standard deviations. Meanwhile the risk sentiment component of FTS for these months moved +0.01, +1.83,, +0.29 standard deviations, respectively. September 2008 reflected a particularly disruptive month with a joint adverse global demand and risk sentiment move driving the flight-to-safety.

S3.1 World prices and the excess risk component of FTS shocks

Figure S.6 traces IRFs from a 1-SD global demand component (G_t) shock (solid), and also a 1-SD shock to the excess risk sentiment component, V_t (dashed) on world prices. The risk sentiment channel drives a significant portion of the response of U.S. interest rates and inflation expectations to flights-to-safety, while commodities are more sensitive to the global demand component. The U.S. Dollar is also much more sensitive to the global demand component than the risk sentiment component of flights-to-safety. After deconstructing FTS into risk and funadmental components, the significant appreciative response of gold to adverse risk shocks is apparent, as is the depreciation of gold when hit with an adverse demand shock. These movements highlight the dual nature of gold as both a safe haven asset (hedges risk aversion) and a commodity with industrial use (procyclical). By contrast, another safe haven asset, the U.S. Dollar, appreciates in response to heightened risk sentiment or lower global demand. So while gold may provide a hedge against rising uncertainty (but not weaker global demand), the U.S. Dollar provides a hedge against both greater uncertainty and weaker global demand.

S3.2 Emerging Markets and the excess risk component of FTS shocks

Figure S.7 shows the impact of a 1-SD global demand component (solid) shock along with the isolated excess risk component (dashed). Qualitatively, both adverse global demand and risk shocks drive emerging market dynamics in the same direction: tighter financial conditions followed by economic contractions. However, quantitatively, emerging market dynamics are much more sensitive to the global demand component compared to a comparably sized risk sentiment shock.

S3.3 Endogeneity and assumptions for separating excess risk sentiment component of global FTS shocks

The reduced-form approach to recover a measure of global excess risk sentiment has the advantage of being convenient, robust and practical. The separation issue, however is subject to complications when taking into account the presence of endogeneity: changing risk perceptions themselves can affect global demand (Bloom [2009], Caballero and Simsek [2020a]) and vice versa. Like asset prices, global FTS shocks, therefore, likely contain both a global demand and risk sentiment component, and the two may be correlated with one another. For the principal-components regression approach to consistently estimate true excess risk sentiment, there are a number of underlying conditions that must be satisfied:

1. The 1st principal component (PC) of commodity price returns reflects global demand.
2. Weak exogeneity of excess risk sentiment.
3. Commodity prices do not pay risk premium on aggregate risk.

I discuss these issues here to acknowledge the limitations associated with them and evaluate how reasonable each assumption may be. The second issue, weak exogeneity of excess risk sentiment implies that global demand is not contemporaneously impacted by *excess* risk sentiment, but can be impacted with a lag. Point 3 follows from points 1 and 2. If the 1st PC of commodity returns is in fact a proxy for global demand and is additionally not influenced by excess risk premia the way financial asset prices are, we should observe that investors in particularly pro-cyclical commodities are *not* compensated for the aggregate risk they bear. Importantly, point 3 is empirically testable.

The 1st PC of commodity price returns reflects global demand

The common factor in commodity prices, to proxy global demand, G_t, must first reflect fluctuations in global demand. Recent and building evidence suggests this condition is validated (Kilian [2009], Kilian and Zhou [2018] Delle Chiaie et al. [2018], Alquist et al. [2020]). Importantly, global demand shocks are also not the same as fluctuations in global activity. Global demand shocks can exhibit more volatility and move significantly faster in reflecting information than, say, real GDP. This means that controlling for global demand is not the same as regressing FTS_t on slow-moving macroeconomic aggregates. Commodity prices exhibit the unique feature of being both tied to the fundamental economy and adjusting at a relatively fast pace (Bailey and Chan [1993], Hong and Yogo [2012]). In fact, some highly financialized commodity markets, like crude oil, respond to information at the speed of liquid financial markets. Less liquid commodity markets may exhibit stickier prices, but often these prices still adjust faster than macroeconomic aggregates.

Weak exogeneity excess risk sentiment

For illustration, suppose FTS shocks can be decomposed into asset price movements reflecting: global demand G_t the component of risk sentiment that affects global demand ρ_t^G (non-excess risk sentiment), and excess or idiosyncratic risk sentiment component V_t,

$$FTS_t = G_t + V_t, \tag{S.8}$$

$$G_t = \widetilde{G}_t - \rho_t^G, \tag{S.9}$$

where

$$cov(G_t, V_t) = 0, \quad cov(\widetilde{G}_t, \rho_t^G) < 0, \quad cov(\rho_t^G, V_t) = 0.$$

Here, total global demand G_t can be decomposed into the "pure" demand effect given by $\widetilde{G}_t$ and non-excess rising risk premia ρ_t^G. Similarly, total risk premia is the sum of ρ_t^G and excess risk sentiment V_t.

A crucial condition to satisfy the assumption of weak exogoneity is that non-excess risk sentiment that impacts global demand ρ_t^G is contemporaneously uncorrelated with excess risk sentiment V_t. Why might this condition be satisfied? Under the rationale that FTS shocks tend source from unique, unusual events. These events are unpredictable. And while the overall "flight-to-safety" signature is similar across these events, the underlying components – global demand, non-excess and excess risk sentiment – driving the flight-to-safety can differ drastically. For example, it may be that the FTS Shock induced by the September 11 terrorist attack was mostly a risk sentiment shock, while FTS during the 2008 Global Financial Crisis were contained a larger global demand shock component. Following the same logic, excess risk sentiment may differ from non-excess risk sentiment from shock to shock in an uncorrelated way. For instance, excess risk sentiment may be more related to technical market conditions or intermediary leverage prior to the FTS shock, while non-excess risk sentiment may be more associated with the degree of macroeconomic uncertainty caused by an unexpected news shock, therefore having a stronger impact on growth.

Why might this condition be violated? Excess and non-excess risk sentiment driving asset prices may be correlated over the business cycle. If excess risk sentiment is determined by intermediary leverage, and that leverage varies systematically with the business cycle, the assumption of excess risk premia and non-excess risk premia being uncorrelated would be violated.

Commodity prices do not pay risk premium on aggregate risk

This condition which follows from the previous assumptions has the advantage of being empirically testable. That is, consistent separation of excess risk sentiment component of FTS shocks from global demand using commodity prices, requires that commodity prices only adjust to changing global demand and *not* to excess risk premia. This is unlike financial asset prices, since asset prices adjust to global demand but are also sensitive to investor risk sentiment. Non-excess risk sentiment *can* impact commodity prices indirectly by causally impacting global demand, but excess changes in risk sentiment do not reflect themselves in commodity prices.

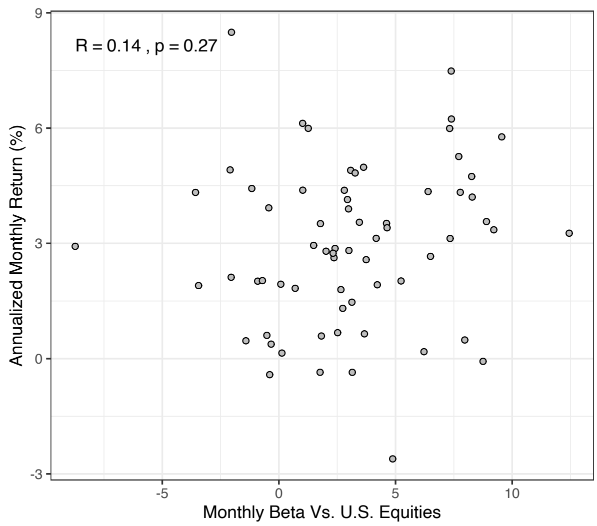
To put another way, commodity investors are not compensated for taking on aggregate risk the way it financial assets compensate holders for bearing the same risk. For this assumption to be violated, heightened risk aversion must directly cause changes to commodity prices above and beyond any effect transmitting through risk aversion's effect on global growth prospects. A violation of this assumption would imply that particularly pro-cyclical commodities exhibit excess returns. I argue that considerable evidence suggests that this assumption is reasonably satisfied. Even at face value, Table S.5 shows annualized returns on commodity ETF investments which invest in futures against the S&P 500 since 2000. Crude oil, copper, and broad commodity prices all exhibit a high degree of procyclical behavior. Despite this, an investment any of these commodities would have yielded negative annual returns over the past decade. Evidence of no aggregate risk premia applies for broad commodity spot returns too. Figure S.5 shows that for a set of 66 spot commodity returns from 2000-2019, U.S. equity betas are essentially uncorrelated with average returns. If aggregate risk premia was priced in the cross-section of commodities, commodities with higher betas would exhibit significantly higher average returns historically.

Table S.5: Commodity Futures Annualized Excess Returns

Date Range	Commodity	Average Return	Daily S&P 500 Beta
2007-2020	WTI Crude Oil	-19.2%	0.76
2011-2020	Copper	-3.5%	0.42
2007-2020	Commodity Basket	-3.9%	0.43
2007-2020	S&P 500	6.16%	1

Daily log returns, annualized. Data taken from ETFs: USO, CPER, DBC, respectively.

Figure S.5: Cross Section of Monthly Commodity Spot Return Betas, 2000-2019



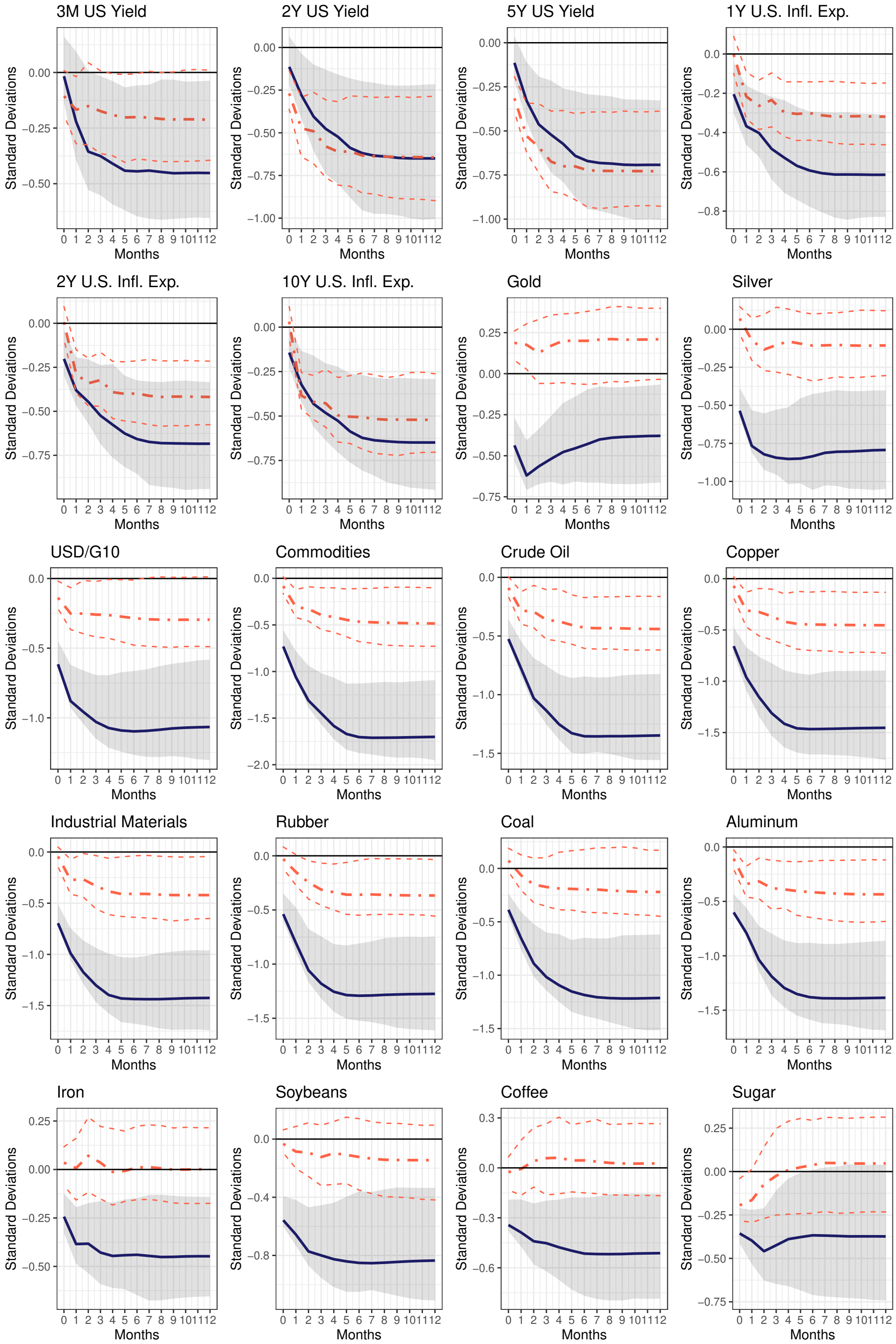
Returns are annualized. U.S. Equity index used is the Wilshire 5000.

More rigorous evidence that commodity investments do not compensate for taking on aggregate risk has been documented over several decades (Dusak [1973], Feldman and

Till [2006], Erb and Harvey [2006]). Rather, commodity risk premia has been linked to producer hedging demand[S2], which is an idiosyncratic supply-side phenomena and other factors like momentum (Hirshleifer [1988], Gorton and Rouwenhorst [2006], Gorton et al. [2013], Szymanowska et al. [2014]). Some commodities like energy and metals are more sensitive to global economic conditions than others (e.g. agriculture). There is some evidence of positive excess returns among energy and metals, but *not* related to associated aggregate risk. Rather, these commodities have higher expected returns during business cycle peaks when inventory is low, supportive of the producer hedging theory (Fama and French [1988], Kucher and Kurov [2014], Duncombe et al. [2018]). This goes in the opposite direction of what standard asset pricing theory would imply.

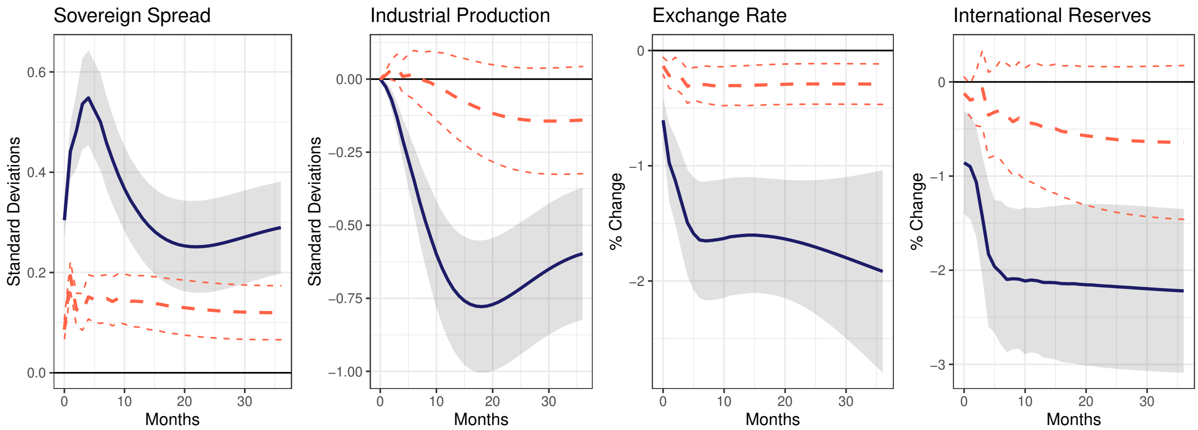
[S2]This comes from The Theory of Storage: in the face of low inventories, commodity prices and volatility rise due to risk of 'stock-out'. As a result, consumers of the commodity store supply at elevated levels. To hedge their production, risk-averse producers must provide additional compensation to counterparties as incentive to enter into commodity futures contracts.

Figure S.6: Risk and Fundamental Components of FTS: Response to a 1-Standard Deviation Global Demand Component Shock (Solid) and Excess Risk Sentiment Component Shock (Dashed)



Cumulative Response (in standard deviations) to a 1-standard deviation risk and fundamental componenet of FTS: Component attributed to the excess risk sentiment component of FTS, $\hat{V}_t$ (dashed) and global demand component, $\hat{G}_t$ (solid) decomposed via Equation S.6. 90% bootstrapped confidence bands.

Figure S.7: Emerging Markets and the Risk and Fundamental Components of FTS: Response to a 1-Standard Deviation Global Demand Component Shock (Solid) and Excess Risk Sentiment Component Shock (Dashed)



Cumulative MG Response (Equation 10) to a 1-standard deviation risk and fundamental component of FTS: Component attributed to the excess risk sentiment component of FTS, $\hat{V}_t$ (dashed) and global demand component, $\hat{G}_t$ (solid) decomposed via Equation S.6. 95% dispersion intervals as computed in Equation 12. Sovereign spreads and Industrial Production response in standard deviations. Exchange rate and international reserves response in percent. Negative exchange rate movement is local depreciation vis-a-vis USD.